How Can AI Recognize Pain and Express Empathy?

Siqi Cao1, 2, Di Fu1, 2, 4, Xu Yang3, Pablo Barros4, Stefan Wermter4, Xun Liu1, 2*, Haiyan Wu5*

1CAS Key Laboratory of Behavioral Science, Institute of Psychology, Chinese Academy of Sciences, Beijing, China
2Department of Psychology, University of Chinese Academy of Sciences, Beijing, China
3State Key Laboratory for Management and Control of Complex Systems, Institute of Automation, Chinese Academy of Sciences, Beijing, China
4Department of Informatics, University of Hamburg, Hamburg, Germany
5Centre for Cognitive and Brain Sciences and Department of Psychology, University of Macau, Taipa, Macau

Abstract—Sensory and emotional experiences such as pain and empathy are relevant to mental and physical health. The current drive for automated pain recognition is motivated by a growing number of healthcare requirements and demands for social interaction make it increasingly essential. Despite being a trending area, they have not been explored in great detail. Over the past decades, behavioral science and neuroscience have uncovered mechanisms that explain the manifestations of pain. Recently, also artificial intelligence research has allowed empathic machine learning methods to be approachable. Generally, the purpose of this paper is to review the current developments for computational pain recognition and artificial empathy implementation. Our discussion covers the following topics: How can AI recognize pain from unimodality and multimodality? Is it necessary for AI to be empathic? How can we create an AI agent with proactive and reactive empathy? This article explores the challenges and opportunities of real-world multimodal pain recognition from a psychological, neuroscientific, and artificial intelligence perspective. Finally, we identify possible future implementations of artificial empathy and analyze how humans might benefit from an AI agent equipped with empathy.

Index Terms—Multi-modal recognition, Face and gesture recognition, Emotion in human-computer interaction, Emotion in human-robotic interaction, Emotional rapport, empathy and resonance, Health implications

1 INTRODUCTION

Pain has been previously described as a physical and psychological negative experience [1]. From an evolutionary perspective, pain expression functions as a psychophysiological reflection with tremendous implications for social relationships [2]. People express their pain in a multimodal manner, which serves to support interpersonal emotional connections such as empathy [3]. Recently, researchers have characterized pain as an uncomfortable sensory and emotional experience [4], [5]. Remarkably, the negative emotional experience is highlighted as one of the fundamental elements of pain [6]. This definition identifies that those previous achievements in emotion recognition can contribute to the investigations in computational pain recognition. Although studies of affective computing have investigated pain, their primary focus is on the recognition of six basic emotions in the human species, and not enough attention is given to pain recognition.

The predominant measure of pain in medicine has long been self-reported. However, the prerequisites for cognitive, linguistic, and social abilities undermine the quality of subjective assessments, especially for young children and patients who have trouble expressing their feelings. Besides, quantitative assessments of pain levels based on physician’s observation is unreliable for details being overlooked. Intuitively, a lack of smile is a significant feature of depressed people [7]. On the contrary, notable cases have indicated that people with depressive disorder can show happy expressions but in a short-lived manner [8]. Consequently, misinterpretations of emotional signs lead to social interaction difficulties.

To sum up, pain assessment has not been sufficiently valid and reliable thus far and more adaptive approaches to pain evaluation are required [9]. Given that clinical evaluations fail to guarantee reliability and objectivity, medical services could benefit from a practical “assistant” for routine pain assessment to reduce the burden on physicians [10], [11], [12]. To achieve this goal, a large body of research in behavioral science and neuroscience has uncovered internal neural mechanisms of pain in the past few decades [13], [14], [15], [16], [17]. More recently, artificial intelligence (AI) has allowed computational and learning approaches based on the external appearance of pain to advance significantly [18], [19], [20], [21]. For example, an AI system capable of understanding and recognizing emotions will be beneficial in various ways, for example, mental health therapy for human beings [22]. Further, the realization of artificial empathy might be possible because of the pain recognition capability in a medical care system. For instance, a system with pain recognition function can instruct an AI agent to seek help under specific circumstances or directly engage in human-like assistant and empathic activities [23]. Empirical evaluation and theoretical studies within this line of research afford remarkable insights to a better understanding of pain recognition from AI and psychological perspectives, which sheds light on future research.
Due to the complexity of pain, research interest in computational pain recognition has primarily focused on techniques from a single unimodality, depending on input from the face, speech, or gesture [24], [25]. However, each modality provides unique knowledge for human emotion, making multimodal pain assessment an exceptionally effective way to the application of pain recognition. Recent evidence has confirmed that multimodality integration technology improves pain evaluation accuracy [26]. It is challenging but promising to explore how multimodality fusion contributes to computational pain assessment more efficiently through interdisciplinary collaboration.

In retrospect, pain is often associated with empathy and noble virtues, such as altruism, from a psychological perspective [27], [28], [29]. People with empathy can recognize and comprehend others’ emotions via experiencing and sharing the emotional states of others [30]. However, a substantial relationship between pain and empathy has not been explored in AI research. An AI agent with human-like empathic responses is considered more caring, likable, trustworthy, intelligent, less dominant, and submissive [31]. Furthermore, empathic reactions help real or virtual agents to establish a trustworthy impression. Despite this, pain state measurement is challenging prior to machines can achieve artificial empathy [32].

Throughout this review, we aim to draw attention to computational pain recognition and gain insight into making multimodal pain assessment an exceptionally effective way to the application of pain recognition. Recent evidence has confirmed that multimodality integration technology improves pain evaluation accuracy [26]. It is challenging but promising to explore how multimodality fusion contributes to computational pain assessment more efficiently through interdisciplinary collaboration.

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TABLE 1
Pain databases

| Database                                      | Type       | Modality          | Subjects                                      | Description                                                                 |
|-----------------------------------------------|------------|-------------------|-----------------------------------------------|-----------------------------------------------------------------------------|
| UNBC-McMaster Shoulder Pain Expression Archive [33] | spontaneous | video             | 129 adults shoulder pain patients             | All videos record the faces of participants with shoulder pain. Participants are instructed to perform a sequence of tests that require motions of limbs in two different scenarios. |
| STOIC database [34]                           | acted      | video             | 10 actors (age 20-45)                         | All videos include basic emotions, painful and neutral expressions.          |
| EmoPain [35]                                  | spontaneous | video, audio, sEMG | 50 subjects (22 chronic low back pain patients and 28 healthy subjects with no history of chronic low back pain) | A multimodal dataset that is completely marked.                             |
| Binghamton-Pittsburgh 4D Spontaneous Facial Expression Database (BP4D) [36] | elicited    | videos            | 41 healthy adults (age 18-29)                 | Social or non-social stimuli are used to elicit pain. All facial expressions are recorded during natural social contact. |
| The “Multimodal Intensity Pain” database (Mintpain) [37] | elicited    | video             | 20 healthy adults (age 22-42)                 | Painful expressions of participants are elicited by electrical pain stimulation. Each video frame is labeled with five pain levels. The pain stimuli that participants received is customized. Total five levels of pain intensity are annotated. |
| The Biovid heat pain database (BioVid) [38]    | elicited    | video, SCL, ECG, EMG, EEG | 90 healthy adults (age 20-65)                 | Twenty-six neonates experience the pain of heel lancing as well as three non-pain stressors. Face, body, and sounds are recorded. |
| The Infant COPE Database [39]                 | spontaneous | image             | 26 neonates (age 18-36 hours)                 | Pain is induced by heat stimulation. Five classes from no pain to pain. Specific pain thresholds (from low to intolerable pain) in the record are determined based on the previous calibration. |
| YouTube Dataset [40]                          | elicited    | video             | 142 infants (age 0-12 months)                 | Pain is induced using a cold pressor test while participants perform different reading and freeform speech tasks. |
| The SenseEmotion Database [41]                | elicited    | video             | 45 healthy subjects                          | A series of neonatal facial expressions videos are included.                |
| X-ITE Pain Database [42]                      | elicited    | video, ECG, SCL, EMG | 134 healthy adults (age 18-50)                |                                 |
| Duesseldorf Acute Pain (DAP) Corpus [43]      | elicited    | audio             | 80 subjects (age 18-70)                       |                                 |
| The iCOPEvid dataset [44]                     | elicited    | video             | 49 neonates                                   |                                 |

Skin Conductance Level (SCL), Electrocardiogram (ECG), Electromyogram (EMG), surface Electromyographic study (sEMG), Respiration (RSP), and Electroencephalogram (EEG).
artificial empathy. First, we review pain recognition from three major modalities: facial expression, speech, and gesture (Section 2; see Fig. 1 left). Then, Section 3 introduces multimodal pain recognition inspired by psychology and neuroscience research (see Fig. 1 middle). Next, Section 4 summarizes current challenges and opportunities for real-world multimodal pain recognition based on the future potential of AI (also see Fig. 1 middle). Furthermore, despite the fact that pain empathy is essential for social functioning, artificial pain empathy has received little attention in prior studies. Thus, we supplement a growing body of knowledge of artificial pain empathy in Section 5 and offer some discussions about how artificial pain empathy could contribute to affective AI research and applications and encourage in the future. Overall, the questions we aim to discuss are: How can AI recognize pain from unimodal or multimodal inputs? Can we build an AI agent with empathy? Is empathic AI necessary? We further explore possible future implementations of artificial empathy and how humans could benefit from an AI agent with empathy (see Fig. 1 right).

2 Pain Recognition

The pervasively discussed research questions of computational pain recognition have been divided into two types: pain detection and pain intensity assessment. Pain detection can be understood as a classification problem, focusing heavily on whether the subject is in pain or not [45]. For practical considerations, researchers have gradually shifted their focus from binary classification problems to regression problems regarding pain intensity estimation [20], whereas pain detection remains challenging and is no easier than intensity assessment [46]. Taken together, a large volume of studies on pain recognition, ranging from static uni-picture analysis [47] to dynamic sequences, have considered the temporal relationship for multimodal information [48], [37], [49], [43], [50].

First, we collected some published databases that serve as the cornerstone of pain recognition, including different modalities (see Table 1). The pain in each database was focused differently, and they can be mainly categorized into three kinds: acted, spontaneous, and elicited (acted expressions were collected from actors; spontaneous expressions were collected from people who have chronic pain or acute pain, and elicited expressions were invoked by audiovisual media or real interpersonal interaction). A significant criticism of the data collected in a lab environment is that people are easy to be motivated to exploit a strategy with which to voluntarily modulate their attention towards painful feelings and enhances pain-related reactions. Zhang et al. [51] have pointed out that when collecting biophysical signals of pain, people tend to change their biophysical signals and thus improve the extent to which their minds are being “read”. It reduces the reliability and validity of the data because of intentionally artificial noise. The noise caused by the abovementioned reason poses a challenge for studies on pain recognition, as this is not a modality-specific problem and may occur in every data collection process.

2.1 Facial Expression

Our faces afford the most informative and reliable cues about mental states, especially emotional information [52], [53]. Researchers developed a well-known Facial Action Coding System (FACS) to identify different facial muscles (action units, AUs) that represent emotions accordingly [54]. Prkachin and Solomon [1] argued that pain expression has a distinct configuration compared to other basic emotional expressions (anger, disgust, fear, happiness, sadness, and surprise). Beyond FACS, Prkachin and Solomon afterward developed a 16-point scale pain assessment standard named after them: Prkachin and Solomon Pain Intensity (PSPI). In addition, an Active Appearance Model (AAM) is also commonly used by researchers to establish facial patterns associated with pain as indirect indicators of computational pain recognition. With AAM, researchers have built a facial expression analyzer being capable of self-adaptive facial muscles classification [9], [46]. With the advent of the criteria for facial features of pain, lots of exploratory and confirmatory studies have sprung up and paved the way for real-life pain recognition [55], [48], [52], [56].

With the introduction of PSPI and Observed Pain Intensity (OPI), classical methods such as the support vector machine (SVM) are common classifiers for facial image classification [57], [58], [46], [59]. Later, a growing body of literature on intensity estimation demonstrates robust evidence of the value of frame-by-frame facial features. For the regression problem of pain intensity estimation, the relevance vector regression (RVR) is a standard method instead of support vector regression (SVR) [55], [60], [61]. Compared to SVR, RVR calculates an additional posterior probability about the uncertainty of each classification and provides a continuous output. Kaltwang et al. [52] improved the precision of the continuous pain measurement by late fusion of three features extracted from a single frame (facial landmark points, PTS; Discrete Cosine Transform, DCT; and local binary patterns, LBPs). However, pain-related facial features can be difficult to identify [19]. There is a growing concern about the ambiguity of pain expressions because they sometimes overlap with other emotions. Yan et al. [56] suggested that some expressive components of pain also belong to other emotions such as disgust and anger. How to maximize data information becomes vital for researchers to make breakthroughs in pain recognition.

Researchers gradually become aware of the role of the dynamic temporal sequence in pain recognition for higher accuracy and ecological validity [62], [48]. Regression is a general method to solve the problem of intensity estimation. However, it has been controversial to determine whether regression of pain intensity estimation is stable. Because of the internal relationship between frames, the regression for pain intensity estimation has apparent drawbacks. As an example, pain and eye closure are positively correlated, while blinking and eye closure have similar facial features when seen in an independent context. Images with eye closure will result in a high estimation of pain intensity, which increases the variance of continuous evaluation. This issue has sparked a trend of exploratory research on the temporal relationships between video frames.
Because of the open access to the labeled databases, most studies focus on supervised learning methods to train the classifier, but the problem of lacking standard labels arises when supervised learning is applied to data from natural scenes.

Research on emotion intensity estimation has attempted to take advantage of semi-supervised methods to reduce costs and improve efficiency. Zhao et al. [64] tried to focus on the changes in facial expression over a short period. The idea is that each expression starts from a neutral stage (baseline) and reaches a peak. Eventually, it will return to a neutral status. Therefore, they proposed a convenient frame-level estimator (Ordinal Support Vector Regression, OSVR), which leverages the ordinal information of different frames within an expression series and the annotations of partial frames. The OSVR consists of ordinal regression (OR) and support vector regression (SVR), which process the ordinal and labeled information, respectively.

Compared with supervised and unsupervised methods, OSVR achieved better results in PSPI score prediction. It is still an open question whether pain intensity estimation is reliable and valid based on the abovementioned features. Also, the process of encoding facial features in videos based on FACS has long been time-consuming. Our best understanding of the facial pain template is AU-based, but the intensity calculation of each AU is subjective. Apart from facial model-based pain recognition, feature learning-based methods are popular recently. Many studies were based on Convolutional Neural Networks (CNN), representing end-to-end applications with a well-established computational feature extraction technique [66]. Zhou et al. [45] focused on facilitating a smooth estimation using dynamic facial properties with a refined Recurrent Convolutional Neural Network (RCNN) framework that works directly on image sequences or video frames. The strength of the RCNN is that it encodes spatial information (CNN-Table 2: Pain recognition based on facial expression

| Database | Feature descriptor | Learning method | Goal | Classifier | Performance  |
|----------|-------------------|----------------|------|------------|--------------|
| UNBC     | AAM landmarks, AUs [9] | Supervised | pain/no-pain | SVM | 78.37% |
| UNBC     | SPTS, CAPP [10] | Supervised | pain/no-pain | SVM | 83.9 |
| UNBC     | AAM landmarks, HoT [57] | Supervised | pain/no-pain | SVR, transfer learning | 0.55 |
| UNBC     | AAM landmarks, DCT, LBP [52] | Supervised | pain intensity | RVR | 0.52 |
| UNBC     | LBP [63] | semi-supervised | pain/no-pain | Transfer learning | 89.5 |
| X-ITE    | PLBP, PHOG [58] | Supervised | pain/no-pain | SVM | 96.9 |
| UNBC     | AAM landmarks, autoencoder [59] | Supervised | pain/no-pain | SVM | 86.1 |
| UNBC     | AAM-warped frame vector sequences [45] | Supervised | pain intensity | RCNN regression | 1.54 |
| UNBC     | self-learned features [64], supervised, semi-supervised, unsupervised | | pain intensity | Ordinal Support Vector Regression | 0.81, 0.95,1,12 |
| UNBC     | VGG_Faces features [65] | Supervised | pain intensity | CNN-LSTM | 0.74 |
| UNBC     | self-learned features [21] | Supervised | pain intensity | CNN | 1.1 |
| MIntPAIN | VGG_Faces features [55] | Supervised | pain intensity | Ensemble Deep Learning Model | 92.26 |
| UNBC     | | | | | 90.5 |

Similairty Normalized Shape or Points (SPTS); Normalized Appearance (SAPP); Canonical Normalized Appearance (CAPP); Histogram of Topographical features (HoT); Discrete Cosine Transform (DCT); Local Binary Patterns (LBP); Second-order standardized moment average pooling (2Standmap); Pyramid Local Binary Patterns (PLBP); Pyramid Histogram of Orientation Gradients (PHOG)
based advantage) along with temporal information in sequence (RNN-based advantage), which yields good results on the fully labeled UNBC-McMaster Shoulder Pain Expression Archive database. In addition, the RCNN overcomes the limitations of manual labeling, which is both time-consuming and expensive. Rodriguez et al. [65] also adopted an end-to-end deep learning model with Long Short-Term Memory (LSTM) to incorporate temporal information. The model outperformed the previous state-of-the-art methods on scores of areas under the curve (AUC), mean standard error (MSE), Pearson correlation coefficient (PCC), and the intraclass correlation coefficient (ICC). A recent study examined whether surrounding information and background interference were obstacles in pain recognition and further increase recognition difficulty. Xin et al. [21] considered the background interference using an adaptive weight distribution on facial regions, which effectively improved the performance.

Although more and more researchers are trying various ways to improve pain recognition technology, pain recognition could benefit tremendously from experience with face recognition. For example, as a remarkable application of the deep learning framework, DeepFace achieves outstanding face verification performance and closes the gap between machine performance and human-level performance [67]. Specifically, researchers have trained a nine-layer deep neural network on the Labeled Faces in the Wild (LFW) dataset, reaching an accuracy of 97.35%. Furthermore, Siqueira et al. [68] improved facial expression recognition on LFW via an ensemble method named Ensembles with Shared Representations (ESRs). ESRs can reduce the residual generalization error, saving considerable training and inference time. However, so far, this approach has only been applied to face recognition, and little is known about how to transfer advanced methods of face recognition to pain recognition due to multiple reasons such as lack of databases. Nevertheless, ensemble-based learning may pave the way to combine several well-established methods in pain recognition. For example, Bargshady et al. [55] exploited an Ensemble Deep Learning Model (EDLM) to classify pain and generate 5-level intensity estimation using the Multimodal Intensity Pain database. Also, this model has been successfully validated for good generalization on the UNBC-McMaster Shoulder Pain dataset.

For future work in pain assessment, ensemble learning combining the output results of multiple models can integrate supervised learning with the latest deep learning framework with convenient tools such as Tensorflow or Pytorch – both already supporting supervised learning. Besides, the state-of-the-art methodology of CNN provides a promising direction for efficient feature extraction, while the efficiency and accuracy balance issue remains. Finally, not only tools are our interests, but the collection and open access of a balanced and accurate pain database are also of great importance.

### 2.2 Speech

While extensive studies have focused on how pain is recognized by facial cues, but few studies have covered how pain is recognized by speech. Traditionally, previous research in speech has focused on blind source separation problems [69], [70] and speech translation [71]. However, it is vital to recognize pain from vocal modality since speech sometimes reveals more than facial expressions (especially for crying babies) [72]. Prior evidence showed that facial structures are unaffected by voice generation, such as the fundamental frequency of phonation and intonation [73]. This separation of speech and facial expressions raises an interesting question of whether we can independently extract pain-related information from speech or consider it a complementary source in pain recognition.

Voice assistants with emotional intelligence can be more natural than those without [22]. Recognizing emotional cues in voices contributes to an empathic dialogue with humans for an AI agent [74]. Ma et al. [75] extensively reviewed the latest progress in empathic dialogue. Empathy in a dialog is critical to improve the usability of human-computer interaction and this is particularly critical and realizable for an AI monitoring pain states of patients in the hospital. They argue that mimicry of others’ emotional states with personalization settings in AI is more user-friendly to show artificial empathy in a real-time conversation. Therefore, with correct recognition of pain from speech, AI can be guided to generate a more empathic vocal interaction.

Generally, a vocal signal can be divided into two aspects (linguistic versus non-linguistic), each with distinct features [76]. On the one hand, the linguistic signal is more complex and subjective than the non-linguistic signal, and natural language may vary across different languages and contexts (i.e., recreation, work). Direct clinical self-reported pain is currently the golden standard for pain assessment. Chaturvedi et al. [77] proposed a concept of fuzzy categorization that blended sentence valence (positive, neutral, or negative) into specific emotion recognition. The method increased precision by 10%-20% compared to baseline methods in classification accuracy. Sometimes, sentence comprehension can be ambiguous, and word polarity judgment is also a big challenge. With a series of prior experiences, people understand communication quickly, and it is primarily based on our top-down cognitive function that is crucial for word polarity detection [78]. This top-down approach facilitates the interpretation of a specific word from sequential contexts [79]. Nowadays, social platforms on the internet are particularly advanced, and substantial natural language data becomes readily available. For example, Twitter and Weibo allow access to enormous text information. Based on the idea of “Wisdom of the crowd”, ensemble learning is gradually applied to sentiment analysis in natural language processing (NLP) on big social data [80]. These surplus learning materials entail labor-saving methods such as semi-supervised learning. A recent study has reached 80% accuracy of emotion recognition and polarity detection on big social data [81]. Notably, text analysis is not as prominent in computational medical diagnostics compared to sentiment analysis on social media platforms. However, in the long run, such NLP-based technological developments are expected to be beneficial for initial, basic online medical consultation.

On the other hand, information also depends on how
we use non-linguistic signs—such as pitch, intensity, and tone. Besides, the non-linguistic transformations (i.e., Mel-frequency cepstral coefficients, MFCCs; filter bank energies, FBEs; linear spectral pairs, LSP) are critical to extract useful indicators for pain recognition [82]. For example, one can subtly convey opposite messages, such as appreciation and sarcasm, by adjusting their tone and stress [83]. The connection between bio-signal parameters of speech prosody and the simultaneous self-reported pain level, suggesting that non-linguistic features indicate internal physiological signals related to pain [84]. Therefore, “how” we speak (non-linguistic) sometimes is even more important than “what” we say (linguistic). Nevertheless, the extraction of speech features and models of pain recognition based on speech is progressing in incremental steps. Nevertheless, a popular audio feature extraction toolkit called OpenSMILE has been proposed to meet the needs of speech feature extraction [85], contributing to this area in the future.

A considerable amount of literature on affective acoustic features pays attention to prosody, voice quality, and spectrum [84]. Methods such as linear discrimination analysis (LDA), regularized discriminant analysis (RDA), SVM, and k-nearest neighbor (K-NN) are commonly used to classify acoustic features [88]. RDA revises LDA by adding a regularized parameter to solve the singularity problem. K-NN can judge the relationships between test samples and the closest training samples in the feature space. However, these features constitute a high-dimensional vector space, and super-seized features lead to a high computational cost for classifier training and testing for recognition. Hence, acoustic feature selection and feature dimensionality reduction is an essential step. Noroozi et al. [89] used the bagging algorithm of random forests (RF) and only randomly selected features to predict the category of input by majority voting on the predictions made by a set of tree classifiers. Background interference has been discussed in face-based pain recognition, but how to reduce background noise in speech-based pain recognition involves purifying audio information [90]. A new noise suppression solution addresses this problem. Yang and Bingham [91] proposed NS (noise suppression) algorithm, which improves all the key indicators, including speech intelligibility, the speech transmission index, the signal-to-noise ratio, and subjective listening experience. However, the effectiveness of this approach on pain recognition needs more investigations.

### Table 3

| Database                  | Classifier          | Accuracy | CCI |
|---------------------------|---------------------|----------|-----|
| Collected themselves [86] | DBFs+LSTM           | 72.3%    | —   |
| Collected themselves [84] | SVM                 | 0.74     | —   |
| Collected themselves [87] | GMM                 | 92.4%    | —   |
| Baby Cry Database [72]    | 30 classifiers in WEKA | 70%      | —   |

Gaussian Mixture Model (GMM); Waikato Environment for Knowledge Analysis (WEKA); Deep Bottleneck Features (DBFs).

In general, pain recognition based on auditory modality is in the initial stages of feature mining, compared to sophisticated facial coding systems. Whether to rely on handcrafted features or computational feature extraction affects the method of choice. Long Short-Term Memory (LSTM) seems to be commonly applied on handcrafted features, while some deep networks are often exploited for a computational extraction of features. In addition, a meta-learning process such as stacked ensemble learning may provide insights for speech-based pain recognition (Fig. 2).

### 2.3 Gesture

The current drive for gesture-based pain recognition has been motivated by recent efforts in computer vision with advanced algorithmic models referring the human visual system. In addition to face cues, motion cues can replace verbal communication [11]. Symbolic movements (such as head nodding) can provide an implicit explanation [92]. Castellano et al. [93] suggested that gestures could be the most effective indicator for pain, followed by speech and facial expressions. Recently, Ruthrof [94] suggested that gesture-based pain recognition can provide valuable complementary knowledge for medical workers and caregivers to attend to patients efficiently. Incorporating body motions into a multimodal pain recognition is advantageous in the long run [95]. Despite a great deal of research on face-based and speech-based pain recognition over the past several decades, there has been very little research intended to expand pain recognition from the perspective of body gestures. One reason for this gap is that a valid interpretation model of body movement is missing while a valid interpretation model functions as a bridge between
pain and gesture units, such as the abovementioned PSPI of facial emotion recognition. A recent study has investigated head movements and postures between pain and non-pain video sequences in three available databases and found significant differences between the two states, indicating that gesture-based pain recognition is feasible. Therefore, as a first summary, research on pain assessment should also consider head movements and postures.

According to emotion recognition from body movements, pre-existing research recognized two aspects of gestures applied to pain recognition. Specifically, researchers put forward some propositional (marker-based) and non-propositional (non-selected marker) movement qualities. Considerable body movements from various body parts can be captured in video sequences, and positional markers are particularly filtered from those body movements [96]. Noroozi et al. [76] summarized that human body models are commonly classified into two types: part-based models and kinematic models. With the combination of the two models, input data is transformed into a feature space for representation learning depending on emotion models to output target emotion. Another study used a multiclass SVM classifier to identify emotions based on three-dimensional skeleton sequences (i.e., postural, kinematic, and geometrical features) [11]. However, gestures can be acquired inherently (nodding to show approval) or extrinsically (in some cultures waving hands to the side to show rejection instead of greetings). Future research should consider the specificity of the cultural context to establish a widely valid model.

As for non-positional movement qualities, Castellano et al. [97] used amplitude, speed, and fluidity of movement to classify eight emotions instead of gesture shape. With valence (pleasant/unpleasant) and intensity, Burgoo et al. [98] focused on context cues and body cues to identify a person’s emotional state from an abstract view. For now, whether to choose a direct (direct feature selection based on raw data) or indirect approach (body models of specific body action units mapping to pain like PSPI) is unstudied. Future studies could compare the two aspects to contribute to the progress of pain recognition based on gestures. Recently, Carnegie Mellon University (CMU) proposed an OpenPose Body Posture Recognition Project, a real-time multi-person 2D gesture estimation based on deep learning without special hardware to acquire data. It is an open-source library based on CNN and supervised learning with Caffe as its framework, and free for download. The project is designed for estimating human body movement, facial expression, finger movement, and other gestures. Multi-target detection can be achieved with high robustness rather than detecting just one target [99]. Even though gestures provide nonverbal cues for communication, yet less attention has been given to the recognition of gesture-based pain. In a nonverbal situation, tracking people’s pain levels through gestures or postures is not easy. Nevertheless, with the developments in motion capture technologies, various motion capture utilities with depth sensors can record good-quality data, which affords future progress in this area [100].

### Table 4

| Database         | Classifier                  | Accuracy  |
|------------------|-----------------------------|-----------|
| Collected themselves [101] | SVM                        | 63%       |
| Collected themselves [102] | K-NN                       | 90.63%    |
| Emo-Pain [103]   | two-level SVM               | 94%       |
| Collected themselves [104] | An interval type-2 fuzzy logic-based classifier | 92.14% |

Taken together, development in basic emotion recognition has attempted to address significant challenges in affective computing over the past few decades. Some achievements for pain recognition via the generalization of methodology from basic emotion recognition also have been observed. Moreover, advances in wearable devices and dry electrode technology have granted researchers access to additional sources of psychophysiological pain indicators such as electroencephalography (EEG) and Electrodermal Activity (EDA) (i.e., monitoring ICU patients) [105], [38]. The importance of bio-signal is that physiological parameters were not correlated with particular emotional states, but instead, they were related to the underlying emotional representation dimensions (valence, arousal, and dominance) (Schlosberg 1954). Therefore, the physiological signal can provide more internal information that could be used for pain intensity estimation [106]. The general knowledge of the unimodal developments in pain recognition reviewed in this paper can support researchers build an optimal multimodal framework in the future. In order to minimize the weakness of a single modality, the strengths of each source should be combined.
2.4 Multimodal Pain Recognition

Mental processes derive from interconnected subsystems in the human brain, and each subsystem contributes to several processes [107]. With the understanding of the human perceptual system, there has been an unprecedented development in computers. An important issue here is how can those already established algorithms replicate the computations in the brain, such as the visual system [108], attention system, and intertwined subsystems [109]. Different brain areas encode information independently but interact with each other [25]. For example, the brain has specialized computational units to represent face and voice information in the occipital and temporal cortex. Meanwhile, the information flow can interact in the transient cortices [73]. Therefore, people can coordinate signals from faces and voices of others. In the past, advances in neurosciences have explored how people integrate multimodal information in the brain [110], [111]. Selective attention in humans, for instance, plays a vital role in the integration of multimodal input [112].

To compensate for limitations of single modality, emotion analysis in human-computer interaction inevitably incorporates multiple dimensions, particularly facial expressions, and speech expressions. Researchers thus have studied robust multimodal feature integration methods [42], [58], [5]. Kächele et al. [26] shown that multimodal information is more advantageous than unimodality to recognize pain when extracting facial expressions, head posture features, and physiological signals in videos. Guillaumin et al. [113] proposed a semi-supervised approach and suggested that the text modality (keywords of a given picture) is of great significance in the improvement of recognition when using SVM. Compared to unimodal systems, multimodal data fusion has improved recognition accuracy substantially [49]. Nevertheless, compared to facial-audio signals integration, only a few studies attempt to investigate body movements or gesture information.

Table 5
State of the art of multimodal pain recognition

| Database            | Modality            | Fusion Type | Classifier  | Accuracy  |
|---------------------|---------------------|-------------|-------------|-----------|
| SenseEmotion        | F+A+Bio             | early/late  | Random Forest | 61/85%    |
| X-ITE               | F+A+Bio             | early/late  | Random Forest | 74.4%/76.8%  |
| BioVid Heat Pain    | F+A+Bio             | early/late  | Random Forest | 78.9%/77.4%  |
| MIntPAIN            | F(RGBD T)           | early/late  | CNN + LSTM  | 36.55%/25.4%  |
| SenseEmotion        | F+Bio               | hierarchical | Random Forest | 71.85%    |
| Recorded in hospital| F+A+G               | Late        | VGG-16+CNN+LSTM | 79%      |
| Recorded in hospital| F+FP+H              | Late        | SNBC+CCC    | 90.5%     |
| Collected themselves| Bio                 | Late        | AdaBoost    | 84%       |

Face (F); audio (A); Bio-physiology (Bio); RGB Depth and Thermal (RGBDT); Gesture (G); Finger pressure (FP); Hand movements (HM); Semi-Naive Bayesian Classifier (SNBC), Circular Classifier Chain (CCC).

Inspired by the human visual system, the successive, nested processing layers of mammalian cortical systems can help to develop deep learning [118], [119]. One advantage of deep learning is its nonlinear computation that can transform raw visual input into a progressively complex set of features, regardless of changes in posture, illumination, or scale. In principle, deep learning can get close to realizing human-like visual performance [120]. Furthermore, with a compelling advantage for multisensory information processing, we can expect intelligent recognition in the real world with more available signals in the future (Fig. 4). The following section introduces possible insights for improvement in pain recognition from a psychological or neuroscientific perspective and interdisciplinary applications.
3 Psychological and Neuroscientific Perspectives

3.1 Memory System

Prior knowledge improves our understanding of the ongoing situation, and prior experience accelerates our learning in the new situation [121]. The prior experience, such as personal medical history, is a precious source of information. People with acute or chronic pain process information differently, which means different types of pain will influence pain expression. For example, a previous study indicated a bias in information processing when experiencing acute pain compared to chronic pain [122]. Therefore, it could be advantageous to provide some secured medical information in an AI agent’s knowledge base in order to support pain recognition for medical purposes. Besides, estimates of pain intensity can be subjective and each individual has his or her personalized sensitivity to pain [123]. When experiencing the same pain stimuli, some people may feel afraid and over-react compared to others. One of the difficulties in pain recognition is the varying emotional expressions towards the same stimuli; that is, people vary in the expression in the same situation [124]. People have different levels of pain expression, so the pattern of responses in prior experiences with similar stimuli is a vital source of learning for pain analysis on specific targets.

How to store short-time information for future retrieval could be based on some principles of the human memory system. For example, humans rely on the hippocampus as a central hub for memory, and the hippocampus is activated when an episodic experience replays during resting and sleeping, which has been considered a process that integrates short- and long-term memory [125]. The brain stores memory in an example-based manner and then “replays” it offline while sleeping and learns from the successes or mistakes that took place in the past [126]. The replay process emphasizes the recirculation of learning based on the reuse of previously collected data. Fig. 5 provides an overall information processing flow illustration within the memory system framework. Specifically, for real-time pain monitoring, a great deal of information captured from different devices converges in the back-end database. Based on previously determined recognition models, LSTM could contribute to instant detection to allow the most valuable signals to process first while other signals are processed later. In the long run, all the data will be trained offline to improve algorithms in specific environments, similar to human episodic memory replay during sleeping, and further apply to the real-time recognition process. In addition, the LSTM, inspired by the working memory framework, is capable of gating information to a fixed operational state and holding it until an acceptable output is required [127]. For multimodal recognition, temporal information needs to be stored appropriately for further processing and continuous analysis, such as sequential video frames and auditory flow [128]. A recent study has shown that the combination of CNN and LSTM successfully detects facial expressions associated with pain in a video sequence. The CNN is designed to extract spatial features and the LSTM is used to store temporal information [18]. Apart from methodology improvement, another branch of research focuses on new feature mining also enriches the pain recognition system. For example, a study has shown that Red, Green, Blue, Depth and Thermal (RGBDT), a newly established feature, contribute to good performance when combining CNN with LSTM for multimodal pain recognition [37].

There is a close relationship between learning and memory. Knowledge and skills are acquired through learning, while memory reflects knowledge [129]. Pain can serve as a motivational incentive because everyone feels aversive about pain, so it is part of an underlying reinforcement learning (RL) model that directs both short-term and long-term behaviors away from harm [130]. In this manner, AI agents embody such capabilities in the context of lifelong developmental learning can determine whether a given situation is good or harmful and use that judgment in pain recognition. We hypothesize that AI for pain recognition can be developed to some extent from an instant analysis of multimodal recognition to incorporate one-shot learning about individual pain experience and learning from situation valence based on individual cognitive patterns (i.e., pain sensitivity).

Fig. 5. Pain recognition systems based on neural processing mechanisms.

3.2 Social Contexts and Environments

Emotion is context-dependent and pain experience may be exaggerated or reduced in different scenarios [131], even though facial information combined with background information can benefit better in expression identification [132]. For example, our discomfort towards aversive stimuli is lower when we are in the company of others compared to when we are alone, referring to the social buffering effect [133]. Meanwhile, high social threats such as high electrocutaneous stimuli administrated by others increase pain intensity and unpleasant feelings [134]. Hammal et al. [135] suggested that context provides substantial information for pain recognition because our location (workspace, hospital, or house) may influence the explicit behaviors that demonstrate our expressions of pain [136]. Therefore, the separation of target and context is of great significance for the precise calibration of pain. For real-life applications, it seems impossible for us to pinpoint the internal source of pain by explicit observation but combining actual
physical history and context-based information leads to a direction.

3.3 Weight Assignment and Data Fusion
Some people rely on speech to express their opinions, while others prefer facial expressions and gestures to express their views. This real-life phenomenon causes an ambiguous interpretation while the analysis of multimodal information is conducive to solving problems. For example, multisensory data fusion has reached considerable advances in accuracy and estimation reliability in fields like navigation. However, two issues to be addressed: 1) whether to choose a simple average of different modalities or a more adaptive weighted algorithm method; 2) which stage will be appropriate for the data fusion? Whether to integrate all the information at an initial stage (early fusion/decision level) or a late stage (late fusion/feature level). Fig. 6 presents a flowchart of how both types of fusion work. Based on neuroscience research, unimodal communication intertwines in lower-level areas, such as the auditory cortex [25] or subcortical regions, including the claustrum and superior colliculus [110]. This evidence provides some insights into the fusion order issue regarding the recognition algorithm. Castellano et al. [93] indicated that the fusion at the feature level provides better results than the fusion performed at the decision level. However, weight assignment is a challenging problem that remains open. One study that focused on the performance between multiple tasks proposed an idea called “elastic” weight consolidation (EWC). This method efficiently shares weights between tasks with a related structure, allowing them to learn multiple tasks without increasing the network capacity [137]. In this way, deep RL networks with the EWC algorithm enable large-scale continuous learning, which may be a promising way to fix catastrophic forgetting [138]. In short, neuroscience has revealed several meaningful mechanisms underlying human cognitive systems, and AI, in turn, has allowed the contributions of those studies to advance substantially.

4 CHALLENGES/OPPORTUNITIES IN MULTIMODAL PAIN RECOGNITION
For the above sections in this paper, at first, the critical aspects of a unimodal- and multimodal- pain recognition system are reviewed. Then, we introduced some established databases, followed by an overview of the recent progress in face-, speech- and gesture-based pain recognition. In terms of robustness, consistency, and implementation requisites, all single modalities have constraints. The philosophy of multimodality is to integrate or combine over at least two modalities (i.e., face, speech, gestures). Multimodal fusion, a vital problem in multimodality applications, is the process of integrating or combining data collected from more than one modality. Despite impressive progress detailed in this field to date, there are noteworthy challenges. A few of the major challenges and opportunities are listed below:

- There is a shortage of balanced data, including targets with different pain levels and real-life big clinical data (i.e., spontaneous painful expressions of different modalities).
- Data diversity increases the difficulty and convergence of recognition. Regarding the natural scenarios, gesture and physiological modalities are often ignored in video classification as well as textual processing. In preliminary investigations on multimodal pain, advancement in classification research about gesture and text (i.e., for shoulder or leg pain) and physiology is crucial for online and remote medical consultations.
- The distinction of various approaches regarding different uses of temporal information still needs to be addressed and discussed.
- The “memory replay” process in the human brain emphasizes learning based on the reuse of previously collected data and training a neural network on stored samples (replaying them again). Combining the advantages of both CNN and LSTM, it is feasible to replicate this idea in computational pain recognition.
- Multimodal pain investigation models ought to be prepared on substantial information from various contexts to construct generalizable models.
- A meta-analysis of diverse methods regarding specific modalities may provide insights into pain recognition. Besides, ensemble learning, which combines several weak classifiers into a robust classifier, is a potential solution to pain analysis progress. The combination of classifiers gets a more robust boundary, reduces the overall error,
and achieves a better classification.

- The current models based on AI will provide insights that can shed light on the study or explanation of human intelligence systems. Understanding the processes of algorithms and brain functions can serve as a mutually complementary contribution to unsolved problems in both domains of algorithmic AI and cognitive neuroscience. Even though some AI agent’s functions are partly inspired by the human brain, this inspiration is limited in detail since the human brain is not yet fully understood.

- The authenticity of human emotion and its explicit and implicit signals is a fundamental step in building assistive AI agents. Detecting the authenticity of emotion is a difficult task here. However, it is a great challenge to establish a sophisticated system for integrating features such as the duration of a smile, facial muscles, voice vibrancy, body gestures, and environmental information.

- The precision, flexibility, and convenience of advanced services require personal information from users. Therefore, models to be developed need to consider the privacy and security of personal information.

5 Future Directions

In the current state-of-the-art, one aspect that an AI agent needs to address is associated with the question “can an AI express empathy?“. There is a long way to go before getting closer to this question. However, could the recognition of pain, which has relatively clear and definite features for an AI agent to learn, lay the foundation of AIs with empathic reactions? There are two steps for an AI to achieve pain empathy. First, the identification of pain; second, the expression of empathy [139]. Our survey in the above sections has reviewed pain recognition progress. In this section, we describe a novel field associated with an affective AI — artificial pain empathy.

5.1 Artificial Pain Empathy

5.1.1 Pain Empathy in Human Research

If we do not understand the human physiological and psychological mechanisms related to complex pain configurations, it will be hard to simulate human-like behavior using artificial intelligence. Therefore, to comprehend pain for computational assisting agents, the integration of psychology and cognitive neuroscience is necessary. Neuroscience emphasizes the shared brain circuits of social and physical functions of pain, indicating a remarkable implication of pain for survival [15]. Thus, the collaboration of social cognitive and affective psychologists and AI scientists have great potential for studying pain empathy on social AI.

The capacity associated with feeling and evaluating the others’ pain state and further understanding them is pain empathy that often prompts prosocial actions [3]. Animal studies suggest that body movement mimicry may be the beginning of the underlying empathy mechanism, which derives from a mirror system in the human brain. The neurons in the mirror system called “mirror neurons” underlies a neuropsychological mechanism of putting oneself in others’ situations, experiencing their emotional states, and resonating with them [140]. Evidence from transcranial magnetic stimulation (TMS) and functional magnetic resonance imaging (fMRI) indicates that when empathy occurs, the mirror neural system activates, contributing to the representation and understanding of others’ inner states. In social interactions, emotional mimicry is crucial since it reflects a desire to connect with another person [141]. To facilitate human-computer interaction or human-robot interaction, researchers have discussed several aspects, such as different forms and manners to induce empathy from human beings. First, the embodiment of an interactive partner influences human mimicry behavior. A physically present and human-like artificial entity tends to induce more mimicry than its virtual non-human counterpart [142]. Besides, emotional mimicry by robots may show its empathic “trait”, improving human-robot interaction experience [143]. Thus, the first step in pain empathy lies in recognizing and imitating facial expressions or gestures in real-time.

Empathy entails co-activation of its affective sharing and mentalizing brain regions. These processes can be reflected in the emotional and self-other perception brain regions, for instance, anterior insula, amygdala, superior temporal sulcus, and temporoparietal junction [144]. These areas are typically characterized as two separate pathways that can be identified as the crucial components of pain empathy: the primary sensory and emotion circuits [145]. Krishnan et al. [14] found that vicarious pain experience (observing others in pain) is neurologically distinct from experiencing physical pain on our own, suggesting that empathy is more cognitive than sensational. But how can AI agents or robots express empathy when they cannot feel pain like humans? Studies on people born with the congenital absence of pain may provide some insights. Danziger et al. [13] found that pain-related brain regions of congenitally pain-free patients are activated, which indicates a shared synchrony aversion with people experiencing pain. Recently, intriguing research on rodents has shown that the anterior cingulate cortex to nucleus accumbens is a paramount neural circuit of a fundamentally social phenomenon — transfer of pain and analgesia [17]. This finding could inspire research into AI and robotics because robots are painless while being with pain-free companions reduces pain perception. The question is perhaps not so much about whether we should realize pain perception in AI and robots, but rather about enhancing the complementary supportive function of a medical treatment assistant. In this manner, AI is expected to reduce pain for patients in a user-friendly way, such as an acceptable embodiment for companionship.

Empathy not only has the intrinsic characteristics of sensibility but also comprises the process of rational top-down cognitive regulation. Based on previous studies, Heyes [146] proposed a dual-system model of empathy: the model includes both the early views that empathy largely depends on the computational process that reflects a bottom-up process (system 1). Meanwhile, it also covers
the control mechanism of empathy that belongs to a top-down process (system II). The two-system model of empathy lays the foundation for the investigations on adjustable empathy from a cognitive perspective and offers the theoretical guidance to artificial empathy of AI assistants or robots. Another aspect is to view artificial empathy from a development perspective of empathy. The algorithms of learning pain empathy are cognitively trainable and probably achievable in AI assistants [23].

5.1.2 Affective AI with Pain Empathy

Being identified in this review, a better understanding is needed to study pain assessment by AI systems. Computational pain computation could be applied to daily human-computer interaction or human-robot interaction to perceive changes in people’s pain states. In a medical situation, empathy is especially important when others are suffering. Besides, pain empathy is paramount for building a bond for cooperation that induces altruistic behavior [147]. There is an intensive debate about the necessity of ethical artificial agent construction [148]. Nevertheless, computational empathy refers to the capacity of computer systems to perceive and respond to people’s views, expressions, and emotions. This concept is presently evolving and gaining a great deal of interest [149].

With each interaction people have with an AI system, an adaptive artificial empathy can be expected [150]. In this paper, we review some available databases in a multimodal affect analysis framework, which may be useful to design algorithms that can generate empathic expressions. However, those databases only include emotional expressions from humans. It may also be crucial for an AI agent to conduct an empathic response to others’ pain experiences. However, researchers have not fully considered an affective AI with proper responses to human emotion. Apart from learning from human-human interaction, an AI system should also learn human behaviors by interacting with real people in an “empathic” way which can be possibly achieved if the data is at hand [151].

5.1.3 Real-world Applications

Life could be more convenient in various situations if an emotional AI companion had appropriate empathetic responses. For example, for a delivery robot, it is vital to avoid pedestrians on the way to its destination. Emotional states contribute to the prediction of pedestrians’ paths. Hence, monitoring the emotional state of pedestrians can improve the user-friendliness of navigation [152]. Moreover, the recognition of pedestrians’ pain states could accelerate health problem identification and shorten rescue time. In an assisted driving situation, the empathy system aims to allow the system to recognize a driver’s negative states and enable the on-board system to take over assistive control of the car at the right time. This measure can prevent accidents caused by pain, emotions, or inattention of drivers [153], which attracts large automobile corporations to study the realization of empathic AI. The Institute for Creative Technologies (ICT) at the University of Southern California created an empathic AI system that functions as a virtual counselor. This system mainly serves veterans with post-traumatic stress disorder (PTSD), requiring computational pain recognition knowledge [154].

Previous studies have attempted to approach a significant issue about how human-computer interaction and human-robot interaction show empathy for humans. For instance, to some extent, human-robot similarity facilitates people’s empathy towards a human-designed machine [155]. Miura et al. [156] also suggested that human-like body movements make it easier for people to empathize. Facial expressions have been primarily utilized as a tool to inform AI systems’ internal states. For instance, Kim et al. [157] created an expression of “bruising” on a robot to investigate the contribution of non-verbal expressions to empathy induction from humans. They found that both speech and bruised color expressed by robots can elicit human empathy towards artificial machines. However, the general findings still need to consider applications to unique people. For example, predictability is necessary for children with autism spectrum disorder (ASD) to socialize. The current study found that the predictability of robot behavior affects how children with autism feel about robots. Therefore, autistic children sometimes can easier communicate with an AI agent, and on the other hand, sometimes have problems in interaction with an AI agent [158]. The study of making virtual reality predictable provides some insights into interactive AI development for a special population as well because a relatively predictable artificial empathic action is more acceptable for autistic children [159].

5.2 Empathy Training for Humans

Generative models inspired partly by human attention mechanisms have recently achieved striking accomplishments. The models emulate training examples and leverage difference pictures and other forms [160]. The images and simulations of human speech generated by models are almost indistinguishable from their equivalents in the real world [161], [162]. Therefore, another potential for an AI agent is to create an iterative loop using a generative model that trains the AI agent. This model can be applied to medical caregivers and people with mental health diseases to improve their pain intensity estimation and empathy. A recent study has indicated the feasibility of training pain detection ability in humans. Participants undergo a 3.5 to 5 hours online training program called the index of facial pain expression (IFPE). After the short training, the capacity of observers to identify psychiatric pain expressions is improved [163]. For people with emotional deficiency, such as children with ASD, who have long been identified as deficient at understanding others’ feelings, empathy training prepares them to fit into everyday social life [164]. Studies have suggested that people with ASD can resonate with others [165]. Hence, an assigned task to artificial agents is to help autistic children establish the ability to perceive, interpret, express, and regulate emotions [166]. For example, a Serbian child who could not speak was able to communicate with his mother after a session with an AI agent (Pantić) under Maja Pantić’s instruction.

In summary, researchers previously dedicated to affective AI with empathic expressions. Therefore, the emerging trend is to build and understand a system with an
empathic ability for AI agents. Moreover, it is possible to train people with functional emotion deficiency in certain situations to cultivate their ability to recognize emotions and express empathy via those adaptive AI assistants.

6 CONCLUSIONS

This paper highlights the potential of multimodal signals for improving pain recognition. With regular monitoring of patient pain levels by clinical staff, patients can obtain timely treatment. Notwithstanding, a computational solution as a complementary AI assistant could be helpful in certain situations. However, some outstanding challenges include noise estimation in unimodal sources, multiple feature extraction, comparison of fusion methods, and establishing balanced and compatible datasets to address the need for real-time applications.

Moreover, an AI assistant should show socially acceptable verbal and non-verbal signals to achieve positive interactions. Although AI can be empathic, its inherent limitations provide challenges regarding understanding, intention, and trust. Exploring affective AI by both psychology and computer science researchers may help to unravel how humans understand others based on sensory and emotional states. Beyond that, artificial pain empathy could enable an AI assistant to become more socially acceptable and generate positive interpersonal interaction. With the pain state analysis and human-level expressions, an artificial agent could be considered not only a binary logic device but also a helpful assistant trained to express empathy and safely interact with humans.

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REFERENCES

[1] K. M. Prkachin and P. E. Solomon, "The structure, reliability and validity of pain expression: Evidence from patients with shoulder pain," Pain, vol. 139, no. 2, pp. 267-274, 2008-10-15 2008, doi: 10.1016/j.pain.2008.04.010.

[2] B. L. Finlay, "The neuroscience of vision and pain: evolution of two disciplines," Philosophical Transactions of the Royal Society B, vol. 374, no. 1785, p. 20190292, 2019. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC690377/pdf/nihms121048.pdf.

[3] B. M. Fitzgibbon, M. J. Giannarou, N. Georgiou-Karistianis, P. G. Enticott, and J. L. Bradshaw, "Shared pain: From empathy to synaesthesia," Neuroscience & Biobehavioral Reviews, vol. 34, no. 4, pp. 500-512, 2010-03-01 2010, doi: 10.1016/j.neubiorev.2009.10.007.

[4] P. Werner, A. Al-Hamadi, K. Limbrecht-Ecklundt, S. Walter, S. Gruss, and H. C. Traue, "Automatic Pain Assessment with Facial Activity Descriptors,"IEEE Transactions on Affective Computing, vol. 8, no. 3, pp. 286-299, 2017-07-01 2017, doi: 10.1109/taffc.2016.2537327.

[5] P. Thiam and F. Schwenker, "Multi-modal data fusion for pain intensity assessment and classification," in 2017 Seventh International Conference on Image Processing Theory, Tools and Applications (IPTA), 28-Nov-1 Dec. 2017 2017, pp. 1-6, doi: 10.1109/IPTA.2017.8310115.

[6] S. N. Raja et al., "The revised International Association for the Study of Pain definition of pain: concepts, challenges, and compromises," vol. 161, no. 9, pp. 1976-1982, 2020.

[7] J. R. C. de Almeida et al., "Abnormal amygdala-prefrontal effective connectivity to happy faces differentiates bipolar from major depression," Biological psychiatry, vol. 66, no. 5, pp. 451-459, 2009.

[8] M. Gavrilescu and N. Vizireanu, "Predicting Depression, Anxiety, and Stress Levels from Videos Using the Facial Action Coding System," Sensors, vol. 19, no. 17 Sep 1 2019, doi: 10.3390/s19173693.

[9] P. Lucey, J. Cohn, S. Lucey, I. Matthews, S. Sritharan, and K. M. Prkachin, "Automatically detecting pain using facial actions," in 2009 3rd International Conference on Affective Computing and Intelligent Interaction and Workshops, 2009-09-01 2009: IEEE, doi: 10.1109/aaai.2009.5349321.

[10] P. Lucey, J. F. Cohn, K. M. Prkachin, P. E. Solomon, S. Chew, and I. Matthews, "Painful monitoring: Automatic pain monitoring using the UNBC-McMaster shoulder pain expression archive database," Image and Vision Computing, vol. 30, no. 3, pp. 197-205, 2012-03-01 2012, doi: 10.1016/j.imavis.2011.12.003.

[11] S. Piana, A. Staglioni, F. Odone, A. Verri, and A. Camurri, "Real-time automatic emotion recognition from body gestures," arXiv preprint arXiv:1402.5047, 2014.

[12] M. Tavakolian and A. Hadid, "A Spatiotemporal Convolutional Neural Network for Automatic Pain Intensity Estimation from Facial Dynamics," International Journal of Computer Vision, vol. 127, no. 10, pp. 1413-1425, 2019-10-01 2019, doi: 10.1007/s11263-019-0191-3.

[13] N. Danziger, I. Faillenot, and R. Peyron, "Can We Share a Pain We Never Felt? Neural Correlates of Empathy in Patients with Congenital Inseparability to Pain," Neuron, vol. 61, no. 2, pp. 203-212, 2009-01-01 2009, doi: 10.1016/j.neuron.2008.11.023.

[14] A. Krishnan et al., "Somatic and vicarious pain are represented by dissociable multivariate brain patterns," elife, vol. 5, p. e15166, 2016/06/14 2016, doi: 10.7554/elif.15166.

[15] M. D. Lieberman and N. I. Eisenberger, "Pains and pleasures of social life," Science, vol. 323, no. 5916, pp. 890-891, 2009. [Online]. Available: https://science.sciencemag.org/content/323/5916/890.long.

[16] C. E. Phelps, E. Navratilova, and F. Porreca, "Cognition in the Chronic Pain Experience: Predelential Insights," Trends in Cognitive Sciences, 2021-01-01 2021, doi: 10.1016/j.tics.2021.01.001.

[17] M. L. Smith, N. Asada, and R. C. Malenka, "Anterior cingulate inputs to nucleus accumbens control the social transfer of pain and analgesia," Science, vol. 371, no. 6525, pp. 153-159, 2021-01-08 2021, doi: 10.1126/science.abe3040.

[18] W. Abedi, A. Sadiq, and I. Ibraheem, "Modified CNN-LSTM for Pain Facial Expressions Recognition," 2020.

[19] M. Pantic, L. J. J. B. Rothkrantz, and B. Sciences, "Machine understanding of facial expression of pain," vol. 25, no. 4, pp. 469-470, 2002.

[20] X. Peng, D. Huang, and H. Zhang, "Pain intensity recognition via multi - scale deep network," IET Image Processing, vol. 14, no. 8, pp. 1645-1652, 2020-06-01 2020, doi: 10.1049/iet-ipr.2019.1448.

[21] X. Xin, X. Lin, S. Yang, and X. Zheng, "Pain intensity estimation based on a spatial transformation and attention CNN," PLOS ONE, vol. 15, no. 8, p. e0232412, 2020-08-21 2020, doi: 10.1371/journal.pone.0232412.

[22] M. Czerwinski, J. Hernandez, and D. McDuff, "Building an AI that feels: AI systems with emotional intelligence could learn faster and be more helpful," IEEE Spectrum, vol. 58, no. 5, pp. 32-38, 2021, doi: 10.1109/mспект.2021.9423818.

[23] O. N. Yalçın and S. J. A. I. R. DiPaola, "Modeling empathy: building a link between affective and cognitive processes," pp. 1-24, 2019.
[24] C. Blais, D. Fiset, H. Furumoto-Deshaies, M. Kunz, D. Seuss, and S. Cormier, "Facial Features Underlying the Decoding of Pain Expressions," Journal of Pain, vol. 20, no. 6, pp. 728-738, Jun 2019, doi: 10.1016/j.jpain.2019.01.002.

[25] J. Davies Thompson, G. V. Elliott, M. Rezk, S. Benetti, M. van Ackeren, and O. Collignon, "Hierarchical Brain Network for Face and Voice Integration of Emotion Expression," Cerebral Cortex, vol. 29, no. 9, pp. 3590-3605, Sep 2019, doi: 10.1093/cercor/bhy240.

[26] M. Kächele et al., "Multimodal data fusion for person-independent, continuous estimation of pain intensity," in International Conference on Engineering Applications of Neural Networks, 2015: Springer, pp. 275-285.

[27] C. D. Cameron, C. A. Hutcherson, A. M. Ferguson, J. A. Schefter, E. Hadjидjandreou, and M. Inzlicht, "Empathy is hard work: People choose to avoid empathy because of its cognitive costs," Journal of Experimental Psychology: General, vol. 148, no. 6, pp. 962-976, 2019, doi: 10.1037/sgp0000595.

[28] E. Fehr and U. Fischbacher, "The nature of human altruism," Nature, vol. 425, no. 6960, pp. 785-791, 2003. [Online]. Available: https://www.nature.com/articles/nature02043.pdf.

[29] E. Staub and J. Vollhardt, "Altruism born of suffering: The roots of caring and helping after victimization and other trauma," American Journal of Orthopsychiatry, vol. 78, no. 3, pp. 267-280, 2008.

[30] T. Singer, "The empathic brain: how, when and why?," TRENDS in cognitive sciences, vol. 10, no. 10, pp. 435-441, 2006.

[31] S. H. Rodrigues, S. Mascaré nhas, J. Dias, and A. Paiva, "A Process Model of Empathy For Virtual Agents," Interacting with Computers, vol. 27, no. 4, pp. 371-391, 2015, doi: 10.1093/iwc/iwu001.

[32] M. F. Jung, "Affective Grounding in Human-Robot Interaction," in 2017 12th ACM/IEEE International Conference on Human-Robot Interaction (HRI), 6-9 March 2017 2017, pp. 263-273.

[33] P. Lucey, J. F. Cohn, K. M. Prkachin, P. E. Solomon, and I. Matthews, "Painful data: The UNBC-McMaster shoulder pain expression archive database," in Face and Gesture 2011, 2011: IEEE, pp. 57-64.

[34] S. Roy, C. Roy, C. Éthier-Majcher, I. Fortin, P. Belin, and F. Gosselin, "STOIC: A database of dynamic and static faces expressing highly recognizable emotions," J. Vis, vol. 7, p. 944, 2007.

[35] M. S. Aung et al., "The automatic detection of chronic pain-related expression: requirements, challenges and the multimodal EmoPain dataset," IEEE transactions on affective computing, vol. 7, no. 4, pp. 435-451, 2015.

[36] X. Zhang et al., "Bpkl-d: A high-resolution spontaneous 3d dynamic facial expression database," Image and Vision Computing, vol. 32, no. 10, pp. 692-706, 2014.

[37] M. A. Haque et al., "Deep multimodal pain recognition: a database and comparison of spatio-temporal visual modalities," in 2018 13th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2018), 2018: IEEE, pp. 250-257.

[38] S. Walter et al., "The biodiv heat pain database data for the advancement and systematic validation of an automated pain recognition system," in 2013 IEEE international conference on cybernetics (CYBICO). 2013: IEEE, pp. 128-131.

[39] S. Brahanm, C. F. Chuang, F. Y. Shih, and M. R. Slack, "Machine recognition and representation of neonatal facial displays of acute pain," Artificial Intelligence in Medicine, vol. 36, no. 3, pp. 211-222, 2006/03/01/ 2006, doi: https://doi.org/10.1016/j.artmed.2004.12.003.

[40] D. Harrison et al., "Too many crying babies: a systematic review of pain management practices during immunizations on YouTube," BMC Pediatrics, vol. 14, no. 1, p. 134, 2014-12-01/ 2014, doi: 10.1186/1471-2431-14-134.

[41] M. Velana et al., "The SenseEmotion Database: A Multimodal Database for the Development and Systematic Validation of an Automatic Pain and Emotion-Recognition System," in Lecture Notes in Computer Science: Springer International Publishing, 2017, pp. 127-139.

[42] S. Gruss et al., "Multi-Modal Signals for Analyzing Pain Responses to Thermal and Electrical Stimuli," Journal of visualized experiments : JoVE,146, 2019.

[43] Z. Ren, N. Cummins, J. Han, S. Schneider, J. Krajewski, and B. Schuller, "Evaluation of the Pain Level from Speech: Introducing a Novel Pain Database and Benchmarks," in Speech Communication; 13th ITG-Symposium, 10-12 Oct. 2018 2018, pp. 1-5.

[44] S. Brahanm et al., "Neonatal pain detection in videos using the iCOPEvid dataset and an ensemble of descriptors extracted from Gaussian of Local Descriptors," Applied Computing and Informatics, 2020.

[45] J. Zhou, X. Hong, F. Su, and G. Zhao, "Recurrent convolutional neural network regression for continuous pain intensity estimation in video," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, 2016, pp. 84-92.

[46] P. Lucey et al., "Automatically detecting pain in video through facial action units," vol. 41, no. 3, pp. 664-674, 2010. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6942457/pdf/nihms1015654.pdf.

[47] D. Simon, K. D. Craig, F. Gosselin, P. Belin, and P. Rainville, "Recognition and discrimination of prototypical dynamic expressions of pain and emotions," PAIN®, vol. 135, no. 1, pp. 55-64, 2008/03/01/ 2008, doi: https://doi.org/10.1016/j.pain.2007.05.008.

[48] S. Broome, K. B. Gleerup, P. H. Andersen, and H. Kjellstrom, "Dynamics Are Important for the Recognition of Equine Pain in Video (2019)," in IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2019: IEEE, pp. 12667-12676, doi: 10.1109/cvpr.2019.01295.

[49] H. Ranganathan, S. Chakraborty, and S. Panchananath, "Multi-modal emotion recognition using deep learning architectures," in 2016 IEEE Winter Conference on Applications of Computer Vision (WACV). 2016: IEEE, pp. 1-9.

[50] P. Werner, A. Al-Hamadi, S. Gruss, and S. Walter, "Twofold-Multimodal Pain Recognition with the X-ITE Pain Database," 2019 8th International Conference on Affective Computing and Intelligent Interaction Workshops and Demos (ACIIW), pp. 290-296, 2019.

[51] S. Zhang et al., "Pain Control by Co-adaptive Learning in a Brain-Machine Interface," Current Biology, vol. 30, no. 20, pp. 3935-3944.e7, 2020/10/19/ 2020, doi: https://doi.org/10.1016/j.cub.2020.07.066.

[52] S. Kaltwanger, O. Rudovic, and M. Pantic, "Continuous pain intensity estimation from facial expressions," in International Symposium on Visual Computing, 2012: Springer, pp. 368-377.

[53] A. C. D. Williams, "Facial expression of pain: An evolutionary account," Behavioral and Brain Sciences, vol. 25, no. 4, pp. 439-+, Aug 2002, doi: 10.1017/s0140525x0200080.

[54] P. Ekman and W. Friesen, "Facial action coding system: A technique for the measurement of facial movement," Palo Alto: Consulting Psychologist Press, 1978.

[55] G. Bangshady, X. Zhou, R. C. Deo, J. Soar, F. Whittaker, and H. Wang, " Ensemble neural network approach detecting pain intensity from facial expressions," Artificial Intelligence in Medicine, vol. 109, p. 101954, 2020-09-01/ 2020, doi: 10.1016/j.artmed.2020.101954.

[56] W.-J. Yan, Q. Wu, J. Liang, Y.-H. Chen, and X. J. j. o. N. B. Fu, "How fast are the leaked facial expressions: The duration of micro-expressions," vol. 37, no. 4, pp. 217-230, 2013.

[57] C. Florea, L. Florea, and C. Vertan, "Learning pain from emotion: transferred hot data representation for pain intensity estimation," in European Conference on Computer Vision, 2014: Springer, pp. 778-790.
[164] S. Baron-Cohen, H. Tager-Flusberg, and M. Lombardo, Understanding other minds: Perspectives from developmental social neuroscience. Oxford: Oxford University Press, 2013.

[165] I. Santiesteban, C. Gibbard, H. Drucks, N. Clayton, M. J. Banissy, and G. Bird, "Individuals with Autism Share Others' Emotions: Evidence from the Continuous Affective Rating and Empathic Responses (CARER) Task," Journal of Autism and Developmental Disorders, 2020.

[166] H. Javed and C. H. Park, "Interactions With an Empathetic Agent: Regulating Emotions and Improving Engagement in Autism," IEEE Robotics & Automation Magazine, vol. 26, no. 2, pp. 40-48, 2019, doi: 10.1109/MRA.2019.2904638.