Supplemental information

Pain recognition and pain empathy
from a human-centered AI perspective

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Pain Recognition and Pain Empathy from A Human-centered AI Perspective

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| Database | Type | Modality | Subjects | Reference | Description |
|----------|------|----------|----------|-----------|-------------|
| UNBC-McMaster Shoulder Pain Expression Archive | spontaneous | video | 129 adults shoulder pain patients | Lucey et al. | 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 | acted | video | 10 actors (age 20-45) | Roy et al. | All videos include basic emotions, painful and neutral expressions. |
| EmoPain | spontaneous | video, audio, sEMG | 50 subjects (22 chronic low back pain patients and 28 healthy subjects with no history of chronic low back pain) | Aung et al. | A multimodal dataset that is completely marked. |
| Binghamton–Pittsburgh 4D Spontaneous Facial Expression Database (BP4D) | elicited | videos | 41 healthy adults (age 18-29) | Zhang et al. | Social or non-social stimuli are used to elicit pain. All facial expressions are recorded during natural social contact. |
| Database                                      | Method                  | Age Range       | Participants | Description                                                                                                                                 |
|----------------------------------------------|-------------------------|-----------------|--------------|---------------------------------------------------------------------------------------------------------------------------------------------|
| The "Multimodal Intensity Pain" database     | 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.         |
| "Mintpain"                                  |                         |                 |              |                                                                                                                                             |
| The Biovid heat pain database (BioVid)       | elicited                | video, SCL, ECG, EMG, EEG | 90 healthy adults (age 20-65) | The pain stimuli that participants received is customized. Total five levels of pain intensity are annotated.                           |
| The Infant COPE Database                     | spontaneous elicited    | image           | 26 neonates (age 18-36 hours) | Twenty-six neonates experience the pain of heel lancing as well as three non-pain stressors.                                              |
| The Infant COPE Database                     |                         |                 |              |                                                                                                                                             |
| YouTube Dataset                              | elicited                | video           | 142 infants (age 0-12 months) | Face, body, and sounds are recorded.                                                                                                                                                          |
| The SenseEmotion Database                    | elicited                | video, audio, SCL, ECG, EMG, RSP | 45 healthy subjects | Pain is induced by heat stimulation. Five classes from no pain to pain.                                                                       |
| The SenseEmotion Database                    |                         |                 |              |                                                                                                                                             |
| Dataset                                | Modality Elicited | Participants | Method                                                                 | Reference |
|---------------------------------------|------------------|--------------|------------------------------------------------------------------------|-----------|
| X-ITE Pain Database                   | video, ECG, SCL, EMG | 134 healthy adults (age 18-50) | Specific pain thresholds (from low to intolerable pain) in the record are determined based on the previous calibration. | Gruss et al. 10 |
| Duesseldorf Acute Pain (DAP) Corpus   | audio            | 80 subjects (age 18-70)          | Pain is induced using a cold pressor test while participants perform different reading and free-form speech tasks. | Ren et al. 11 |
| The iCOPEvid dataset                  | video            | 49 neonates                     | A series of neonatal facial expressions videos are included.       | Brahnam et al. 12 |

Skin Conductance Level (SCL), Electrocardiogram (ECG), Electromyogram (EMG), surface Electromyographic study (sEMG), Respiration (RSP), and Electroencephalogram (EEG).
| Title                                                                 | Reference       | Journal                  | Performance                                                                 |
|----------------------------------------------------------------------|-----------------|--------------------------|----------------------------------------------------------------------------|
| Using AI to Detect Pain through Facial Expressions: A Review          | De Sario et al. 13 | Bioengineering            | Pain detection: 80.9% to 89.59%; Pain intensity estimation: 51.7% to 96%; Distinguishing real and faked pain: 85% to 88% |
| Artificial intelligence to evaluate postoperative pain based on facial expression recognition | Fontaine et al. 14 | European Journal of Pain | Predicting pain intensity: 53% with a mean error of 2.4 points; Sensitivity to detect pain ≥4/10: 89.7%; Sensitivity to detect pain ≥7/10: 77.5% |
| Incorporation of 'Artificial Intelligence' for Objective Pain Assessment: A Comprehensive Review | El-Tallawy et al. 15 | Pain and Therapy         | Sensitivity in pain detection (Fontaine et al.): 89.7%; Sensitivity for severe pain detection (Fontaine et al.): 77.5%; Accuracy for pain intensity estimation (Fontaine et al.): 53%; Accuracy for shoulder pain estimation (Bargshady et al.): 89% to 94%; Accuracy for self-induced shoulder pain estimation (Barua et al.): 95.57% |
| Pain Assessment based on fNIRS using Bi-LSTM RNNs                    | Rojas et al. 16  | IEEE                     | Bi-LSTM model achieved the highest accuracy: 90.6%                           |
| Identification of potentially painful disc fissures in magnetic resonance images using machine-learning modeling | Kerstin et al. 17 | European Spine Journal   | Mean accuracy for pain classification: 69%; Precision: 71%                 |
| The Analysis of Pain Research through the Lens of Artificial Intelligence and Machine Learning | Nagireddi et al. 18 | Pain Physician           | No specific accuracy or AUC mentioned; summary of various studies.          |
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