The Fifth Edition of the Automated Assessment of Pain (AAP 2025)

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ABSTRACT

Pain communication varies significantly among individuals, some are highly expressive, while others demonstrate stoic restraint and offer minimal verbal indication of discomfort. Substantial progress has been made in identifying behavioral indicators of pain. A growing body of literature highlights measurable indices of pain through facial expressions, vocalizations, body movements, as well as physiological and neural responses. To enhance the reliability of pain monitoring, automated pain assessment has emerged as a promising approach. Although available datasets remain limited, they are steadily increasing, helping to drive research forward. Despite notable progress, this field is still in its early stages. The 5th edition of the AAP workshop continues to seek to highlight current research and foster interdisciplinary collaboration and discussion to accelerate progress in this important area.

CCS CONCEPTS

• **Applied computing** → Life and medical sciences; Health informatics; • Human-centered computing → User interface design; User models

KEYWORDS

Pain, Health Informatics, Human Centered Computing, Clinical Datasets.

1 Introduction

Pain is not merely an unpleasant sensory experience but also a complex affective phenomenon, shaped by individual history, contextual influences, and personal modes of expression, as emphasized in the revised definition by the International Association for the Study of Pain (IASP) [1]. Despite its pervasive impact, pain remains one of the most intricate but under-explored affective states, representing both a significant challenge and a critical opportunity to expand the scope of affect recognition theories and tools. Our workshop aims to support research on the computational and automatic assessment of pain.

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Progress has been made in identifying behavioral markers of pain [2–4]. A substantial body of research demonstrates that a set of facial movements can encode pain intensity across the lifespan, not only in humans but also in several non-human species [3]. In addition, vocalizations [5], physiological and neural responses [6], and body movements [7,8] have all been identified as containing indicators of pain. These findings underscore the multimodal nature of pain expression, revealing that no single modality can fully capture its complexity.

Pain assessment has traditionally relied on self-report, yet this approach is not always feasible or reliable. Certain populations, such as infants, individuals with advanced cognitive impairment, or non-verbal patients, may be unable to communicate their pain effectively. In other cases, frequent self-monitoring (e.g., through pain diaries) can inadvertently heighten distress and reinforce focus on discomfort. Recent advances in low-cost sensing technologies for the automatic detection of pain-related markers [6] are helping to address these challenges, enabling both in-hospital and out-of-hospital personalized pain assessment and management support [9–10].

Recent research has demonstrated significant progress in analyzing facial expressions [11,12], vocalizations [13], body movements [14], as well as physiological and neural responses [15,16]. Yet pain is fundamentally multimodal, highly variable, culturally shaped, context-sensitive, and deeply personal. Consequently, automated pain assessment systems must navigate, complexity, ambiguity, adapt to individual baselines, and confront pressing ethical issues related to autonomy, privacy, and informed consent. The increasing, though still limited, availability of datasets capturing both experimentally induced and clinically observed expressions of pain (e.g., [18–23]) is contributing to foster research in this area as well as facilitating a shift from unimodal to increasingly multimodal approaches in automatic pain recognition.

The fifth edition of the Automatic Assessment of Pain (AAP) Workshop, held in 2025, provides a dedicated forum for presenting new research, identifying open challenges, and fostering interdisciplinary collaborations. It responds to the growing demand for computational methods capable of integrating and interpreting multimodal signals relevant to the expression and experience of pain. The workshop also addresses the critical need for greater awareness of, and contributions to, datasets that can drive progress in this emerging field. AAP'25 brings together researchers from affective computing, health technologies, neuroscience, machine learning, and human-computer interaction to collectively advance the state of the art in pain assessment, ensuring that technological developments remain grounded in the lived experiences of the individuals they are designed to support. The list of papers presented at the workshop is provided below.

2 Workshop Content

After a double-blind peer review process, the fifth edition of the International Workshop on Automated Assessment of Pain (AAP) includes thirteen accepted papers covering a range of models for AAP.

- *Canonical Time Series Features for Pain Classification by Boda et al. [24].*

The paper investigates the effectiveness of the Canonical Time-series Characteristics features (catch22) for pain classification using multimodal physiological data. Multiple machine learning algorithms were evaluated for two classification strategies (binary classification and three-class classification).

- *When Features Matter More than Sequence: A Case for Tabular In Context Learning in Pain Classification by Jonker et al. [25]*

The paper compares a feature-based ensemble (TabPFN) and a hybrid deep learning approach (Transformer with Features) for measuring pain levels from multimodal physiological data. The TabPFN model outperforms the deep model suggesting that complex deep learning models are not always superior, especially when dealing with small, noisy datasets.

- *Feel the Pain: An Interpretable Multimodal Approach for Physiological Signal-Based Pain Detection by Tazin et al. [26]*

The paper presents an interpretable machine learning pipeline for pain detection from physiological signals relying on extensive features from 10-second windows. XGBoost with domain-driven features performed best among the classification models.

- *Tiny-BioMoE: a Lightweight Embedding Model for Biosignal Analysis by Gkikas et al. [27]*

The paper presents a lightweight pretrained embedding model Tiny-BioMoE pretrained on over 4 million biosignal samples. The authors conducted an in-depth analysis of how different modalities perform under various visual representations, as well as the effectiveness of fusing different representations and modalities for pain measurement.

- *The AI4Pain Grand Challenge 2025: Advancing Pain Assessment with Multimodal Physiological Signals by Rojas et al. [28]*

The paper presents the AI4Pain 2025 multimodal physiological dataset and challenge. It describes the data collection procedures and recording including the setup for the four bio Signals (EDA, Resp, BVP, SPO_2) as well as the application of the pain stimuli in three pain levels (no pain, low pain, high pain).

- *Multi-Representation Diagrams for Pain Recognition: Integrating Various Electrodermal Activity Signals into a Single Image by Gkikas et al. [29]*

The paper presents a pipeline that uses multiple representations of electrodermal activity as a diagram of six waveform representations and used a hierarchical Vision Transformer encoder optimized for the measurement of pain intensity levels.

- *PainXtract: A Multimodal System for Multiclass Pain Classification Using Physiological Signals by Gupta et al. [30]*

The paper presents PainXtract, a multimodal MLP based model leveraging handcrafted features extracted from physiological signals using NeuroKit2 library for pain intensity measurement.

- *A Multimodal Deep Learning Exploration for Pain Intensity Classification by Pinzon-Arenas et al. [31]*

The paper presents a three-stage evaluation of two deep learning techniques for three-level pain classification: a convolutional neural network (CNN) and a long short-term memory network (LSTM), as well as a combination of both into three hybrid architectures.

- *Explaining Pain by Combining Deep Learning Models and Physiology-Driven Ensembles using PPG, EDA, and Respiration by Javierre et al. [32]*

The paper presents a hybrid three-stage approach for objective pain assessment that combines deep learning for pattern discovery with machine learning for robust classification. The paper combines deep learning with explainable AI (Grad-CAM and feature ablation) to identify temporal patterns across multimodal physiological data.

- *EnsembleIQ-Pain: Intelligent Cluster Calibration for Personalized Pain Detection by Agarwal et al. [33]*

The paper presents EnsembleIQ-Pain, a personalized pain detection framework leveraging multimodal physiological signals. Extensive comparison was conducted to compare the proposed architecture with benchmarks including shallow machine learning algorithms and classic deep learning algorithms.

- *Painthenticate: Feature Engineering on Multimodal Physiological Signals by Datta et al. [34]*

The paper presents Painthenticate, a feature engineering on multimodal physiological signals for pain measurement. The paper focuses on data preprocessing, systematic feature engineering, and the comparison of several machine learning models.

- *Investigation into Unimodal Versus Multimodal Pain Recognition from Physiological Signals by Elebiary et al. [35]*

The paper investigates unimodal versus multimodal machine learning approaches (1D-CNN and hybrid CNN-LSTM) for pain recognition using physiological signals and investigates both early and late fusion strategies for integrating multiple physiological signals.

- *Efficient Pain Recognition via Respiration Signals: A Single Cross-Attention Transformer Multi-Window Fusion Pipeline by Gkikas et al. [36].*

The paper proposes a Resp-Encoder architecture and a pipeline that leverages respiration as the input signal and an efficient cross-attention transformer with a multi-windowing strategy for pain measurement.

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