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# A Survey on Automated Pain Recognition and Assessment Using Multimodal

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***Abstract**: Practical pain assessment is essential in clinical practice. However, conventional methods for pain assessment depend primarily on patients' self-reports, which are not feasible for non-communicative individuals, such as neonates and unconscious patients. Automated pain recognition presents a viable alternative that utilizes multimodal approaches integrating physiological signals and behavioral patterns. This survey examines recent advancements in Artificial Intelligence-based pain assessment techniques. We review current methodologies, challenges, and applications in healthcare. Furthermore, we discuss critical limitations, including dataset availability and model interpretability. Finally, we propose future research directions to enhance automated pain recognition systems' accuracy and clinical integration.*

***Keywords**: Automated pain assessment, Pain recognition, Assessment, Artificial intelligence, Machine learning, Natural language processing, Deep learning, Robotic, Multimodal, Behavior signals, Physiological signals.*

## 1. Introduction

According to the International Association for the Study of Pain (IASP), pain is an unpleasant emotional and sensory experience that is associated with, or resembling what is related to, potential or actual tissue damage. As demonstrated by conditions such as neuropathic and psychogenic pain (which could arise even in the absence of direct damage to the tissue), this definition emphasizes the multifaceted nature of pain, which includes both emotional and sensory components [1, 2]. In clinical settings, self-reporting is the foundation of conventional pain assessment techniques. However, these techniques are inherently subjective and could be unreliable, especially for people with communication problems [3]. Automated pain recognition systems use Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), and computer vision for enhancing the accuracy, objectivity, and efficiency regarding pain evaluation [4]. As explained in [5], these automated systems are more effective and efficient. Latest developments in AI-driven pain assessment are used multimodal methods which examine several pain indicators, such as based (facial expressions, linguistic analysis and, body movement) and physiological based (Galvanic Skin Response (GSR) or ElectroDermal Activity (EDA), ElectroMyoGraphy (EMG), ElectroCardioGram (ECG), Respiration Rate (RR), etc.) to be combinable. These technologies have great promise for enhancing pain detection, self-management, and prediction. As such, they can help doctors to deliver personalized pain treatment. In spite of encouraging advancements in this domain, most of the AI-based pain assessment techniques remain in the pilot stage and need more validation via extensive clinical trials prior to general use in medical settings [6].

Accurate pain identification is still a major problem in the healthcare sector [7]. This is especially the case for patients who are unable to adequately express their pain, such as small children, severely ill people, and adults suffering from dementia. The main objective of this study is to present concise and recent methods for identifying pain in these patients. This is enabled by the analysis of multiple signals, such as voice, facial expressions, poses, gestures, and physiological signals. Therefore, these systems aim to assess pain level in individuals who cannot express it effectively. The specific objectives of this study include the following:

- We highlight the limitations of solely relying on patient self-reports to assess pain, especially in cognitively or verbally disabled people. In healthcare settings, this study advocates for automated pain identification using DL and ML techniques, based on temporal and spatial recognition.
- The study describes the development of promising and reliable models for pain recognition using advanced technologies such as computer vision, DL, and robotics. We show that these models are accurate and adaptable for diverse patient groups.
- To standardize and improve pain detection procedures, this paper provides basic information regarding various pain intensity scales, accessible pain databases, as well as performance evaluation criteria for automated pain assessment techniques.
- Through the use of multimodal data and advanced AI techniques, we show that improvements are observed in pain recognition accuracies for patients from diverse backgrounds and with various conditions. This research recommends the design and implementation of real-time pain assessment systems capable of delivering accurate and timely assessments that enhance patient care and support clinical decision-making.

This work offers an extensive overview of automated pain recognition systems, as well as assessments applied with multimodal techniques. The presented work is structured as follows: Section 2 details the methodology used to identify and select the most relevant studies in the field, as well as the procedures followed for collecting the most relevant studies and research questions. Section 3 reviews the related works research on pain recognition and assessment. Section 4 reviews publicly available datasets for pain recognition training and validation of ML models, and Section 5 gives background on AI methods such as DL, Natural Language Processing (NLP), ML, computer vision, and robots utilized in pain assessment. Section 6 discusses the benefits of AI-based pain detection and assessment systems, while Section 7 highlights the limitations and challenges related to pain assessment driven by AI.

Furthermore, Section 8 explored the multimodal approaches used for pain measurement, while Section 9 addresses future directions of research. Towards the end of this paper, Section 10 display the most important analysis and discussion. Finally, Section 11 presents the conclusions of the study.

## 2. Methods

### 2.1. Study selection

Along with manual screening of relevant sources, a thorough literature search utilizing many academic databases was undertaken. Such databases included Google Scholar, ResearchGate, Web of Science, Scopus, and IEEE Xplore. Initially, we found 4500 studies on automated pain evaluation. To guarantee relevance, these studies were filtered depending on their emphasis on efficient pain assessment techniques. This yielded 50 research papers that were then selected for in-depth analysis. The selected papers were examined more closely to create a suitable classification that would help to clearly define their contributions and methodological differences. Based on the utilized models, Fig.1 presents the main categories that were obtained.

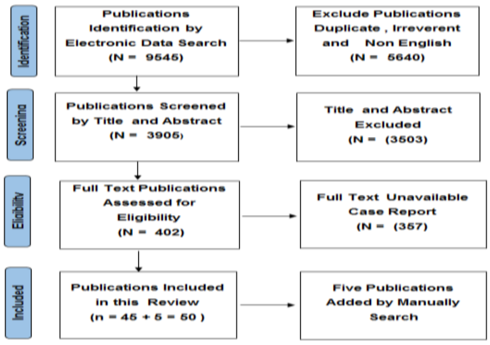


Fig. 1. PRISMA flowchart of included researches [3]

### 2.2. Research questions

A modern suite of pain-detection technologies, which include datasets like physiological signals, voice, facial expressions, and robotics, has been employed, and a set of questions was developed for the purpose of exploring them in detail. The central question of our research is: To what extent can the integration of multimedia data, hybrid deep learning techniques, temporal dynamics analysis, and real-time robotic applications enhance the accuracy and efficiency of systems for detecting varying pain levels and delivering immediate, adaptive responses?

The sub-questions of this study examine: (1) the extent to which facial expressions can achieve high accuracy in detecting mild to moderate pain levels; (2) the role of physiological measurements and audio signals in enhancing the detection accuracy of severe pain levels; and (3) the potential of multi-layered (hybrid) deep learning architectures to outperform traditional methods in classifying pain levels. In addition, the study investigates the impact of incorporating temporal variations in physiological signals and facial expressions on improving the recognition of transitions between pain levels, compared to static data analysis. Finally, it explores the feasibility of developing robots with real-time processing capabilities that can detect pain with high accuracy and deliver adaptive responses within seconds.

## 3. Related works

Over the recent past, pain assessment and recognition have attracted a lot of interest in academia and industry. Many databases used by researchers (many of which have been obtained from hospitals or deliberately intended for this use) have been combined with different AI approaches. Among these, multimodal datasets are quite important. This is because they play an accurate and unique function in pain recognition and assessment. The latest research developments in this field are described in this section. This includes discussions on automated pain assessment and recognition systems that incorporate several ML and AI methods (such as facial expression analysis, voice recognition, multimodal data fusion, such as fuzzy logic systems designed for rehabilitation). Table 1 gives a summary of some noteworthy studies in this domain.

Fontaine et al. [8] have shown that facial expression analysis driven by AI could help doctors assess pain level and identify pain intensity. Using a DL system (ResNet-18 CNN), their research examined 2810 facial expressions from 1189 patients taken before and following surgery. Using the Numeric Rating Scale (NRS) in the range of 0 to 10, the technique was trained to predict pain intensity. With a mean error of 2.4 points, the model correctly identified pain intensity in 53% of cases in an external test set, including 120 photos. With accuracies of 44.9% and 17.0% for the same pain thresholds, the system attained sensitivities of 89.7% for pain levels ≥4/10 and 77.5% for ≥7/10, respectively, greatly exceeding nurse estimations.

A model based on patch and transfer learning is presented by Barua et al. [9] for the classification of various pain degrees from facial images. In order to split facial images into dynamically sized horizontal patches (referred to as shutter blinds), they used a light-weight network called DarkNet-19, which had already been trained on ImageNet 1K. The model achieved over 95% accuracy using a facial action coding system on datasets from the University of Northern British Columbia-McMaster Shoulder Pain Expression Archive (which includes 4 pain intensity levels labeled by human experts), and Denver Intensity of Spontaneous Facial Action Database.

Using facial ElectroMyoGrams (EMG) from the BioVid Heat Pain Database, Kelati et al. [10] have developed an ML-based pain degree classification method. To assess continuous levels of pain, this method examined facial EMG signals (from zygomaticus and corrugator muscles). The results indicate that this technique attains an outstanding 99.4% accuracy in identifying pain tolerance from baseline (P0 vs. P4). In addition, it is free from subject bias and hence this approach provides insightful analysis.

A study by Benavent-Lledoet et al. [11] concentrated on the relationship between facial expressions and data taken from biomedical sensors. With single-frame analysis, they obtained over 96% accuracy in pain estimation utilizing state-of-the-art computer vision techniques and benchmarks such as BioVid Heat Pain Data-base and UNBC-McMaster Shoulder Pain Expression Archive. For visual tasks, their techniques used transformer-based architectures. As such, their study established a new benchmark in pain recognition accuracy.

To evaluate postoperative pain in children, Fang et al. [12] have presented a vast-scale Clinical Pain Expression of Children (CPEC) dataset. Using the Children Pain Assessment Neural Network (CPANN), a unique DL architecture with 82.1% accuracy and 73.90% macro-F1 score on the CPEC data-set is developed.

Ghosh et al. [13] have developed an innovative healthcare framework-based sentiment analysis system for pain detection. This system employed statistical and DL-based feature analysis to assess pain intensities from facial images. The evaluation was accomplished using two face pain expression databases (2D Face-set database with pain expression and UNBC-McMaster shoulder pain). The term "sentiment analysis" is used to mean the analysis of emotions or emotional expressions, specifically those related to pain, through the analysis of facial expressions.

Safavi, Patel and Vinjamuri [14] have presented an effective DL model based on Mix Transformer (MiT) blocks developed from the SegFormer architecture. This study's main focus was on the recognition of facial expressions for pain assessment. Based on the FER2013 dataset, this approach resulted in greatly lowering the latency and computational costs. This model also yielded a higher level of accuracy compared to other related state-of-the-art methods.

Mendu et al. [15] have carried out an investigation of how well a voice interface might promote MBSR (i.e., Mindfulness-Based Stress Reduction). They have found out that such interfaces could lead to enabling people who have limited motor ability to participate more successfully in strategies of pain treatment. Their interviews with facilitators have given insightful analyses of voice interfaces' usability and possibilities in healthcare.

Lu, Ozek and Kamarthi [16] created a transformer-encoder DL system for pain level classification based on physiological signals. In this method, the authors have presented a potential solution for the classification of pain intensity. This is because it included a number of modules of feature extraction, and its performance exceeded current models on the BioVid pain dataset.

Sabater-Garriz et al. [17] developed an automated system for pain assessment based on DL for cerebral palsy patients. They trained Neural Networks (NNs) using the InceptionV3 model on a recently selected CP-PAIN dataset and produced encouraging results with a 62.67% accuracy and 61.12% F1 score.

Zheng and Lin [18] aimed at facilitating the tasks of pain classification, which is why they have evaluated many hybrid models, like CNN+BiLSTM, CNN+LSTM, CNN+GRU, and CNN+Transformer. Results have shown that the performance of the CNN+Transformer model was superior to other methods, yielding an 0.795 accuracy, pointing out transformer-based methods' efficiency in the task of pain recognition.

Hausmann et al. [19] created a YOLO-based system of facial expression detection that has been based on the Neonatal Intensive Care Unit (NICU) for the purpose of neonatal pain prediction and classification. This system was successful in achieving 8.60% Mean Average Precision (MAP) and a 21.20% increase in Area Under the ROC Curve (AUC) for automatic classification of neonatal pain. Results have shown a notable accuracy improvement when compared to the assessment of hand pain by NICU nurses.

Kristian et al. [20] combined facial traits with voice data for the purpose of developing an infant pain detection method. Extensive information from audio spectrograms and facial images provided the DL autoencoders (convolutions and variational autoencoders) with the ability for classifying pain levels. Multi-modal fusion results exceeded the results that have been provided by using single-modal techniques..

Sandeep and Kumar [21] proposed a novel AI model combining ResNeXt and Mediapipe techniques to identify and assess pain levels in autistic children. The system used CNNs to classify facial expressions in real time. The results were integrated to yield a more accurate pain recognition system.

Talaat et al. [22] focused on detecting emotions (such as pain or anger) in autistic children. The developed emotion recognition system used deep CNNs and autoencoders for facial feature extraction. High classification accuracy was obtained with pre-trained models such as ResNet, MobileNet, and Xception.

Aliradi, Chenni and Touami [23] developed a hybrid model for pain assessment utilizing CNNs and an enhanced XQDA algorithm. When tested on the UNBC-McMaster dataset, the approach demonstrated improved accuracy over previous methods. This is indicative of the robustness of their model for pain recognition.

Using an exoskeleton, Abdallah and Bouteraa [24] have presented a fuzzy logic-based pain detection system that adjusts rehabilitation parameters for patients. These personalized rehabilitation strategies have shown good outcomes in clinical trials.

Wahab and Dutta [25] have created a model of facial expression pain identification. For image extraction, hybrid feature engineering approaches such as DenseNet 201, MobileNet V3, and Liquid NN were utilized. The outcomes indicated that the model performed quite well in pain classification using face images.

Gutierrez, Garcia-Ortiz and Villegas-Ch [26] introduce a multidisciplinary technique for a pain detection system that integrates paralanguage and facial gestures. Their hybrid model obtained high recall, precision, and specificity. As such, this model serves as a sensitive approach for pain recognition using AI methods.

Based on the discussions above, it is evident that numerous techniques have been developed, ranging from innovative DL models to multimodal systems and fuzzy logic applications. All these techniques are geared towards the enhancement of pain assessment. Each of the studies in Table 1 demonstrates some advances in the continuous development of automatic and effective pain recognition systems.

In most research focused on the recognition of pain, the techniques are classified into two types: unimodal and multimodal. Unimodal techniques are simpler in design and processing as they depend on a single channel of data such as physiological signals, facial expressions, or even the voice, albeit such techniques are limited in capturing the complex essence of pain. Multimodal techniques, on the other hand, seek to synthesize data from several sources, hence merging physiological signals with videos and audios to provide a fuller picture that improves the models' reliability and accuracy [27].

It is worth noting that the classification we used in this section, distinguishing between unimodal and multimodal approaches, primarily relates to the type of input data, rather than the specific technologies or algorithms used for processing or classification. In terms of technology, whether traditional machine learning algorithms or deep learning or fusion models are used, they can be applied to both approaches, depending on the nature of the available data and the objective of the study.

## 4. Datasets

The pain recognition and evaluation field rely heavily on publicly available datasets, which provide annotated data for training and validating ML models. Through the provision of annotated multimodal data, these datasets are foundational to pain recognition and evaluation research. They enable advancements in facial expression analysis, physiological signal processing, and multimodal data fusion. As such, they contribute to the development of automated pain assessment systems. Researchers can leverage these datasets to explore new methodologies and enhance the reliability and accuracy of pain recognition technologies.

In this section, we discuss some of the commonly and majorly utilized databases in pain recognition research. In addition, we discuss their key features and applications. According to [28] and [29], the major datasets are UNBC-McMaster Shoulder Pain Expression Archive database [30], BioVid [62, 31], BP4D-Spontaneous database [32], BP4D+ database [33], MIntPAIN database [34], COPE database [35], YouTube dataset [36], Infant Cry Signals Database (IIIT-S ICSD) [37], EmoPain database [38, 39], SenseEmotion [40], and X-ITE painA [41]. The study in [28, 42] provides the URLs and updates for these datasets.

- **UNBC-McMaster shoulder pain expression archive database.** This dataset includes facial expressions of pain from 12 individuals experiencing shoulder pain. It contains both visual and physiological data annotated for pain intensity levels. It is primarily used for facial expression recognition and pain intensity classification [30].
- **BioVid heat pain database.** This dataset contains video and physiological data (such as GSR, ECG), and EMG collected during heat-induced pain stimuli. It is mostly applied to analyze physiological responses to heat pain and classify pain intensity [31, 43].
- **BP4D-spontaneous database.** This dataset comprises of spontaneous facial expressions linked to pain sensed by people subjected to pain stimuli. Training models able to identify spontaneous facial expressions in pain recognition systems [32] benefits from this.

- **BP4D+ Database.** Along with physiological signals, BP4D+ is an expanded form of BP4D-Spontaneous database with extra facial expression recognition among different people [33].
- **MIntPAIN database.** This database is focused on pain in children and provides a collection of facial videos and images of children going through pain. This dataset is utilized to investigate pediatric pain recognition, particularly in nonverbal children [34].
- **COPE database.** This dataset features facial videos and images of people exhibiting pain. It specifically emphasizes controlled experimental conditions. It enables models to evaluate pain depending on facial expressions in several controlled settings [35].
- **YouTube dataset.** This dataset consists of YouTube videos with annotations on the expression of pain. It covers many real-life events, especially in unconstrained environments [36]. It is useful for training models on real-world facial expressions of pain.
- **Infant Cry Signals Database (IIIT-S ICSD).** This dataset holds cry signals from newborns together with annotations on pain degrees depending on vocalizing patterns. Models trained on this dataset help in identifying infant discomfort levels depending on their crying patterns [37].
- **EmoPain dataset.** This is a multimodal dataset of behaviors connected to chronic pain. This dataset was collected by positioning four surface ElectroMyoGraphic (sEMG) sensors on the back to track muscle activation from eighteen Inertial Measurement Units (IMUs). This dataset has been deployed in ML applications for pain detection and classification. In addition, it helps in the evaluation of human activity identification in rehabilitation environments, as well as protective actions in patients with chronic pain [38, 39].
- **SenseEmotion.** This is a multimodal dataset for emotion recognition and pain detection. It includes data collected from various sensors such as facial expression cameras, physiological sensors (for instance, skin conductance and heart rate), and sometimes audio or text inputs. The dataset is frequently utilized for training ML models to detect and classify emotions, including pain. Through the analysis of patterns in the collected data, this dataset can be used for real-world scenarios and applications for pain detection and healthcare monitoring [40].
- **X-ITE pain.** This is a comprehensive multimodal dataset designed explicitly for pain detection and analysis. It is part of the larger X-ITE project, which focuses on understanding and quantifying pain through various physiological and behavioral signals. The dataset is widely used in research for developing and validating ML models for pain recognition [41].

Table 2 summarizes the properties of these pain recognition research databases, some of which are publicly available, while others are not. In addition, it offers key details on data types (such as facial expressions, physiological signals, and cry signals), sources, and specific pain assessment applications. These datasets are essential for the development of reliable pain detection systems. Researchers can utilize them to explore new methodologies and improve the accuracy of automated pain recognition technologies. This is especially important when combining multiple modalities (such as facial expressions, physiological signals, and voice analysis) for comprehensive pain assessment. In our survey, analysing the database is not just a technical issue. Still, a focal concern in assessing the rigor of prior studies, appreciating their shortcomings, and crafting future research strategies based on nuanced and substantive data is a far more thoughtful consideration.

Table 1. Summary of current approaches

| Ref. Year | Method | Datasets | Type of data | Classification of AI technique | Limitation | Results |
|---|---|---|---|---|---|---|
| [8] 2022 | ResNet-18 CNN | Collected dataset from 1189 patients before and after surgery | Facial expressions | DL-Computer Vision (unimodal approaches ) | -Model accuracy issues<br>-Real-world application challenges<br>-Integration into clinical settings requires further validation and regulatory approval | Accuracy 0.53%<br>Recall 89.7%, 77.0%, 44.9%, 17.0% |
| [9] 2022 | DarkNet19. KNN | -Denver Intensity of spontaneous facial action<br>-McMaster shoulder pain expression | Facial images | ML-DL-Computer Vision (unimodal approaches ) | -A shallow classifier (KNN)<br>-Increase computations | Accuracy 0.95% |
| [10] 2022 | KNN | BioVid Heat Pain | Physiological signals (EMG) | ML (unimodal approaches ) | -Highlights the potential of FEMG only.<br>-Limited generalizability<br>-Real-world deployment may require additional optimization.<br>-Feature selection bias | Accuracy 99.4% |
| [11] 2023 | - Logistic regression<br>- SVM<br>- Decision trees<br>- CNNs<br>- Transfor-mer | -UNBC-McMaster<br>- BioVid Heat Pain | Physiological signals & Video face shoulder pain expression | ML-DL-Computer Vision (multimodal approaches) | - Subject variability<br>- Dataset constraints<br>- Over-fitting risks<br>- Contextual challenges | Accuracy 94.95% 87.61% 93.88% 92.87% 80.75% 91.72% 93.77% 91.9%<br>Precision 72.91% 71.34% 76.65% 79.45% 94.67%<br>F1 Score 94.61% |
| [12] 2023 | CPANN | CPEC | Face and gestures | DL-Computer Vision (multimodal approaches ) | - Dataset imbalance<br>- Age-related variability<br>- Single-modality data<br>- Pain labeling subjectivity | Accuracy 82.1%<br>F1 score 73.9 % |
| [13] 2023 | - HOG<br>- LPB<br>- CNN<br>- HOG-LBP-CNN | - UNBC-Mc Master<br>- 2D Face Set Database | Face images shoulder pain expression | ML-DL-Computer Vision (unimodal approaches ) | - The reliance on facial expressions alone<br>- Potential biases in the datasets<br>- Computational complexity of DL | Accuracy 79.14% 80.29% 81.54 % 83.71% |

Table 1 (c o n t i n u e d)

| Ref. Year | Method | Datasets | Type of data | Classification of AI technique | Limitation | Results |
|---|---|---|---|---|---|---|
| [14] 2023 | Transformer | - FER2013<br>- AffectNet<br>- RAF-DB<br>- CK+<br>- SFEW | Facial Expression Recognition (FER) | DL-Computer Vision (unimodal approaches) | - Dataset bias<br>- Computational cost<br>- Generalization to real-world scenarios | Accuracy 75.2%<br>F1 score 0.74% |
| [15] 2023 | Amazon Alexa ecosystem | Collection dataset | Motor gestures voice interfaces | DL (multimodal approaches) | - Small sample size<br>- Lack of end-user perspective<br>- Limited generalizability | Accuracy 54.8% |
| [16] 2023 | Transformer encoder MSCN | BioVid heat pain | Physiological signals (ECG, EMG, and GSR) | DL (multimodal approaches) | -Difficulty in classifying lower pain levels<br>-Only EDA signals used<br>-Generalization challenges | Accuracy 85.34% |
| [17] 2024 | DL (AlexNet, VGG16, VGG19, ResNet) | - Mint<br>- Delaware<br>-UNBC-McMaster<br>-CP-PAIN d | Facial recognition patients with cerebral palsy video | DL-Computer Vision (unimodal approaches) | -Dataset limitations<br>-CP-PAIN dataset is small<br>-Lower performance<br>-Imbalanced training data<br>-Not being capable of collecting self-reports from the majority of individuals who have CP | Accuracy 62.67 %<br>F1 score 61.12 % |
| [18] 2024 | -CNN + Transformer<br>-CNN + GRU | BioVid Heat Pain | Physiological signals (ECG, EMG, and GSR) | Fusion DL Models (multimodal approaches) | - Limited focus on multimodality<br>- Do not deeply evaluate the challenges of deploying these models in real-time | Accuracy 0.795 0.559 |
| [19] 2024 | YOLO | USF-MNPAD-I | Facial expression on (NICU)-Video | DL- Computer Vision (unimodal approaches) | -Generalization issues<br>- Challenges in lower-quality data<br>-Limited availability of neonatal datasets<br>-NICU environment complexity | Accuracy 62.7% |
| [20] 2024 | -STFT<br>- Autoencoders<br>- CNN | Collection dataset includes 189 videos | Combined facial traits with voice data ML- Fusion | DL Models Computer Vision (multimodal approaches) | -Limited data size<br>-Substantial computational resources | F1 score 0.980245 |
| [21] 2024 | CNN | -Autism-specific facial expression dataset | Facial Expressions in Real Time | DL-Computer Vision (unimodal approaches) | -Dataset limitations<br>-Real-world implementation problem<br>-Generalization challenges | Accuracy 0.95% |
| [22] 2024 | DCNN | A dataset of autistic children's facial expressions | Facial expressions Images | DL-Computer Vision (unimodal approaches) | - Small dataset<br>- Facial expression complexity<br>-Autistic children's unique expressions make recognition more challenging | Accuracy 95.23%<br>Precision 93.2%<br>Recall 94.21%<br>F1 score 93.31% |

Table 1 (c o n t i n u e d)

| Ref. Year | Method | Datasets | Type of data | Classification of AI technique | Limitation | Results |
|---|---|---|---|---|---|---|
| [23] 2024 | -XQEDA - Deep learning | UNBC-McMaster shoulder biovid heat pain database | Physiological signals& Video face shoulder pain expression | DL-Computer Vision (multimodal approaches) | -Dependence on facial expressions only -Dataset constraints -Computational complexity | Accuracy 0.85% |
| [24] 2024 | -OSCS – Fuzzy logic | Electromyography (EMG) signals | Physiological Signal (EMG) | Machine Learning (unimodal approaches) | -Single-subject study -Sample Size: The study involved only one participant | Accuracy 0.83% |
| [25] 2024 | Liquid Neural Networks (LNNs) Hybrid DenseNet 201, MobileNet V3 | DISFA | Facial expressions Images | DL-Computer Vision (unimodal approaches) | -Dataset constraints -Sensitivity to variations in image quality | Accuracy 0.97% and other metrics 97% |
| [26] 2024 | CNN-LSTM | Data collection captured facial gestures and paralanguage (sound) | Paralanguage, facial gestures, and sound | DL-Computer Vision (multimodal approaches) | - Need to collect more diverse datasets - Some signals might not have been represented adequately in the dataset | Precision 0.90% Recall 0.92% |

## 5. Artificial intelligence techniques for pain assessment

AI has increasingly been used in pain recognition, evaluation, and management. In addition, it offers a spectrum of approaches that are fit for various clinical and scientific applications. Since diverse methods may produce varied degrees of accuracy in several pain assessment situations, the particular goal and dataset mostly determine the performance of any particular AI model [6]. Recent studies have demonstrated the promising potential of AI-driven pain detection, achieved through the analysis of physiological signals and behavioral indicators. Physiological signals of interest include EEG, ECG, GSR/EDA, EMG, EDA RR, and others. On the other hand, behavioral indicators include facial expressions, vocal characteristics, and body movements [44, 45] as mentioned above. To develop predictive algorithms capable of improving pain assessment, tracking pain progression, and even predicting treatment outcomes, ML and DL models process various data sources [11, 46]. Such data sources include self-reported pain scores, physiological biomarkers, and electronic medical records.

The following sections explore key AI techniques utilized in pain assessment and their contributions towards the enhancement of patient outcomes and clinical decision-making. These AI techniques are well classified in Fig. 2.

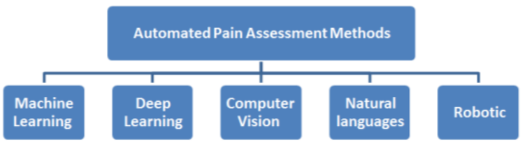


Fig. 2. Automatic pain assessment methods using AI

Table 2. Summary of popular pain recognition research datasets

| Ref. | Database | Subjects | Data modalities | Stimuli | Annotation |
|---|---|---|---|---|---|
| [30] | UNBC-McMaster shoulder pain | 25 adult shoulder pain patients | Video of face (low resolution, including social interaction/talking) | 200 range of motion tests with affected as well as unaffected limbs | Self-report (VAS, sensory and affective verbal scales), affected/ unaffected limb, Observer-assessed Pain Intensity (OPI), FACS coding |
| [31, 43] | BioVid heat pain | 90 healthy adult subjects (age 20-65) | Video of face, ECG, EDA, EMG (trapezius muscle; corrugator and zygomaticus for part B) | 14 k heat pain (four intensity levels _20 repetitions two parts 90 participants); emotion elicitation posed expression | Stimulus (calibrated for each person) |
| [32] | BP4D-Spontaneous | 41 healthy adult subjects (age 18-29) | Face video (color and 3-D) | 41 cold pressor tasks; emotion elicitation | Stimulus, FACS coding |
| [33] | P4D+ | 140 healthy adult subjects (age 18-66) | Video of face (colour, 3-D, thermal), respiration rate, heart rate, EDA, and blood pressure, | 140 cold pressor tasks; emotion elicitation | Stimulus, FACS coding |
| [34] | MIntPAIN | 20 healthy adult subjects (age 22-42) | video of face (depth, colour, thermal) | 2 k electrical pain (40 stimuli in four intensities two trials 20 participants) | Stimulus (calibrated per person), self-report (VAS) |
| [35] | COPE | 26 neonates (age 18-36 hrs) | 204 photos of the face | 60 heel lancing for blood collection; non-painful stimuli | Category (cry, pain, rest, air puff, or friction) |
| [36] | YouTube | 142 infants (age 0-12 months) | 142 videos with audio | Immunizations (i.e., injection) | FLACC observer pain assessment |
| [37] | IIIT-S ICSD | 33 infants (age 3-24 months) | 693 audio cry samples | Immunizations (i.e., injections) and other causes of pain; non-painful cry causes | Category annotated by the doctors and parents (discomfort, pain, hunger/thirst, and three others) |
| [38, 39] | EmoPain | 22 chronic lower back pain patients (age = 50) + 28 healthy controls (age = 37) | Audio, video, motion capture, sEMG (trapezius, lumbar paraspinal muscles) | Physical exercises (scenarios of therapy) | Self-report, pain intensity assessed by naïve observers from the face, presence of pain behaviours that are assessed by the experts from the movement of the body |
| [40] | SenseEmotion | 45 healthy adult subjects (age = 26) | Video of face, audio, ECG, EDA, sEMG (trapezius muscle), RSP | 8 k heat pain (three intensity levels 30 repetitions two stimulus sites 45 participants); emotion elicitation | Pain and emotion stimuli (pain calibrated for each person) |
| [41] | X-ITE painA | 134 healthy adult subjects (age 18-50) | Video of face (colour, thermal), video of body (colour, depth), audio, ECG, EDA, sEMG (corrugator, trapezius, zygomaticus) | 24 k phasic pain, 804 tonic pains (both by heat and electrical stimuli, each with three intensity levels) | Pain stimulus (calibrated for each person) |

## 5.1. Machine learning

Pain is inherently subjective, and hence traditional assessment methods often lack consistency and reliability. As such, ML has emerged as a powerful method for pain recognition and assessment. These machine learning algorithms provide innovative solutions to the challenges of objective pain measurement. ML techniques, particularly the ones leveraging computer vision, NLP, and physiological signal analysis, have shown considerable potential in the enhancement of the efficiency and accuracy of pain evaluation. Automated pain assessment is made possible by ML algorithms' ability to find trends and extract significant features from many datasets.

In pain recognition tasks [3, 11, 13], several ML models have been effectively employed. Such models include Random Forests (RFs), Support Vector Machines (SVMs), Decision Trees (DTs), Logistic Regression (LR), Histogram of Oriented Gradients (HOG), and Local Binary Patterns (LBP). Using facial expression analysis, physiological data, and vocal characteristics (such as weeping noises in children), new ML-based models have been developed for pain identification. As explained in [47], high accuracy rates (more than 92%) have been obtained with these methods. This has helped in differentiating pain from non-pain situations. ML-driven approaches combine automated facial expression detection and analysis for pain evaluation. This has proved very helpful for non-communicative patients, such as those with severe dementia [48]. In addition to the machine learning methods which are mentioned in [9, 10, 20, 24], which were described in Section 3.

Whether the studies relied on single-type techniques, such as KNN [10], LR, SVM, and DT [11], HOG and LBP features [13], STFT [20], and fuzzy logic [24]. In contrast, hybrid techniques that combine multiple approaches, such as using a pre-trained DarkNet19 model on the ImageNet dataset to extract deep features from images and then classifying them using KNN, as in [9], or integrating HOG-LBP-CNN techniques [13]. All these approaches have demonstrated significant effectiveness and tangible success in the task of pain assessment and recognition.

### 5.2. Deep learning

DL is a subfield of AI and ML that can learn hierarchical patterns from complex datasets. Based on these capabilities, DL has attracted a lot of interest in pain recognition as well as assessment. According to [3], DL methods are especially successful in evaluating facial expressions, physiological data, and patient-reported outcomes. As such, these methods offer new opportunities for automated and objective evaluation of pain.

CNNs, Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), and Transformer models, amongst several DL architectures, showed exceptional performance in pain assessment. Because the CNNs are used extensively for facial images and video sequences' evaluation, they dominated the pain recognition field through analysis of facial expressions [11, 14].

Besides facial analysis, DL approaches were used for analysing physiological signals, including Heart Rate Variability (HRV), Electro-EncephaloGraphy (EEG), and ElectroDermal Activity (EDA). As such, they offer objective pain bio-markers. By collecting complicated features from such signals, DL models excel in allowing more data-driven and exact pain assessment [49].

Multi-modal DL techniques have been introduced for the purpose of improving the pain detection systems' robustness and accuracy. These techniques can analyze facial expressions, physiological signals, and audio features, providing a more all-encompassing pain perception knowledge [11, 16, 18, 21, 23]. Nevertheless, problems like data scarcity, subjectivity, and model interpretability still pose major obstacles that must be overcome. These challenges played the role of impediments towards full DL's potential exploitation in clinical applications [17, 18, 20, 21, 23].

### 5.3. Computer vision

In pain recognition and assessment, Computer Vision (CV) is becoming a crucial transformative technology. It provides an automated study of visual cues, including body movements, facial expressions, and other nonverbal pain signals. CV is especially helpful in clinical settings, pediatric care, and elderly care. In these environments, CV systems offer objective, real-time pain assessments through the incorporation of cutting-edge technologies such as DL and image processing.

CV has transformed pain evaluation and detection by providing precise, automated, and real-time techniques for visual cue analysis. DL models and multimodal techniques are enabling CV systems to provide more accurate and efficient pain evaluations both in non-clinical and clinical settings. DL and CV approaches, for instance, could help identify and classify facial expressions (such as frowning or grimacing) and other behavioral indicators linked to pain [3, 8, 50].

One well-known application of CV is the automated facial expression assessment of pain severity. This has proven successful in the identification of clinically important pain levels during rest and during activity, especially in postoperative settings and among young people. Facial expressions are among the most consistent and well-investigated markers of pain. By means of DL, CV systems could identify and evaluate even the minute variations in face features, suggesting discomfort [11, 14]. Bodily movements, facial expressions, and posture are also important pain indicators. This is particularly in nonverbal patients, such as newborns or old people with dementia. CV systems are quite good in analyzing such physical cues to project pain levels. Automated facial expression assessments have demonstrated to favorably correlate with patients' self-reported pain levels to reinforce the efficiency of CV in real-world pain assessment [38]. Nevertheless, issues such as subjectivity, privacy problems, and model interpretability should be resolved before CV can fully benefit pain management.

Despite the promising results in this field, some challenges and limitations still exist, such as subject variability, dataset constraints, overfitting risks, contextual challenges, limited data size, and substantial computational resources [11, 20, 21, 23]. Many researchers in this field have been addressing all these issues.

### 5.4. Natural Language Processing (NLP)

NLP is the study of the interaction between computers and human language. It allows machines to comprehend, process, and create human language meaningfully. NLP has helped to greatly progressed the automated analysis of patient-reported outcomes, clinical notes, and even social media posts in pain assessment. In so doing, it has enabled more efficient and accurate pain evaluations [3, 51].

NLP approaches became indispensable pain recognition and assessment tools. This is facilitated by textual data analysis, including patient feedback, clinical documentations, and patient-generated content from platforms like social media. Using advanced NLP models provides healthcare professionals with the ability to better understand patients' pain experiences, which leads to the enhancement of diagnostic accuracy and facilitation of developing customized and effective plans of treatment. These customized pain treatment approaches were shown to help in patient care improvement.

Nevertheless, NLP use in pain evaluation has presented challenges, such as data subjectivity in patient reports, privacy issues, and possible data bias, which are problems that need to be resolved to fully maximize NLP in clinical environments, which will be helpful as well to foster accurate and ethical use of those tools in healthcare [52].

Quite often, patients use words to express their discomfort, whether via clinical surveys, digital health applications, or diaries. As such, NLP models can be utilized for evaluating location, pain, and type severity in those descriptions. As it has been explained in [14] and [53], electronic health records (EHRs) include useful information on the pain experiences of patients in the clinical notes. Through the extraction and analysis of this data, NLP models can support doctors in decision-making. In the majority of cases, pain is accompanied by emotional suffering, which might be documented by using textual data. Through patient narratives, NLP models can detect pain-related sentiments and emotions. From social media data (like duration, location, and severity of pain), NLP can be helpful in the extraction of information on these aspects. Social media platforms offer a wealth of information for helping to grasp population-level pain experience. Through analysing posts and comments, NLP models can detect pain-related trends and sentiments [14, 54, 55].

### 5.5. Robotics

Robots are programmed machines designed for autonomously executing particular tasks, interacting with their surroundings, and supporting different applications. Robotics became one of the highly promising and inventive solutions in the recognition and assessment of pain [3]. This is more pronounced in healthcare settings where, in some cases, conventional approaches are difficult or limited (like in pediatric care, elderly care, or non-verbal patients). Through integrating cutting-edge sensors, ML algorithms, and Human-Robot Interaction (HRI) methods, robots have become increasingly important in pain spotting and assessment in patients.

As discussed in [14], robotics represents a rapidly expanding research field in pain management. Robotic pain therapies were investigated extensively, and their integration into medical environments has been gaining momentum, which is fuelled by robotics' ability in the interpretation of multimodal data (like physiological signals, behavioral patterns, and environmental inputs). Together with DL approaches, robotics offers reliable and rapid pain level estimates [56].

Social robotics and Robotic Patient Simulators (RPSs) represent major innovative developments that can be utilized for generating high-fidelity, facially expressive robots to be used in clinical environments. Those robots replicate human interaction, hence improving pain assessment capacity through more dynamic and realistic patient responses. Even though progress was made in the front, present commercially produced RPSs still have limitations that are related to fidelity and usability, mostly as a result of their lack of expressive expressions necessary for efficient clinical contacts and diagnosis.

The use of robotics in the management of procedural pain and chronic pain disorders has yielded some benefits. Here, different robotic technologies are applied to discriminate between anxiety and felt pain, hence guiding therapies. Most recent studies, such as social assistive robots, are effective in the evaluation and management of pain for people who have dementia, as well as for their family and caregivers. These robots can offer real-time monitoring and combine behavioral as well as physiological data to offer exact pain assessments [57].

Depending on several cues such as video, images, audio, and vital signs, robots may deduce pain levels using sensors and AI methods. The integration of technologies such as NLP, computer vision, and AI in robots has facilitated more automated, accurate, and real-time pain management in both non-clinical and clinical environments. Nevertheless, ethical issues, accuracy, and accessibility present some challenges that must be resolved in this field. As discussed in [3] and [58], widespread acceptance and effective application of robotics in healthcare depend on addressing these critical problems.

From the studies reviewed subsections above for Section 4, it is evident that techniques of deep learning are concluded and analysed the certainly have the edge in recognizing pain because they can retrieve higher mentally models from the profoundly complex and multi-dimensional pieces of data over traditional methods in a machine learning context crafted focusing on SVM, KNN, and LR models, these classic systems heavily depend on hand crafted features, whereas deep learning models can access only if they have been earlier pre-trained on large amount of data to learn appropriate representation, regardless of whether it is physiological data like an ECG, EMG, and GSR signal, videos showing the face and its bodily movements, or even voice recordings that illustrate speech intonement. Thus, training on these mixed forms of data through a multimodal learning approach invariably offers deep learning techniques higher performance than those relying on only computer vision, language, or audio processing. With the addition of biosignals, videos, and audio, convolution, recurrent, and transformer neural networks can learn spatio-temporal dependencies from various neural signal deep learning systems and non-linear interactions from the aforementioned signal streams, thus enhancing the confidence in the system's pain level predictions. From a practical viewpoint, these models represent an early version of a robotics system that understands and communicates with the patient. Advanced models like these demonstrate how adaptable AI is in treating different kinds of pain and provide individualized and efficient ways for pain identification and management [9, 11, 14, 16, 21, 22, 26].

The pain recognition process has changed with the invention of deep learning, shifting from a population of patients to a single patient approach. Focusing on chronic pain management, it is imperative to understand someone's pain from different modalities and neural signals. These biosensors and deep learning can assist in shifting the old paradigm of chronic pain to a more modern approach. Emphasizing the patient's experience in pain over the AI's reasoning and data prioritizes the person on the healthcare continuum, a vital change in the technologically dominated era we live in. Chronic pain has a number of different perceptions and meanings, and deep learning systems must understand this idea of multifactorial-ness.

## 6. Need for pain detection and assessment systems

The benefits of pain detection and assessment systems span clinical, technological, and societal domains. These systems leverage advancements in AI, ML, and multimodal data integration to provide objective, real-time, and scalable solutions for pain assessment [59]. For instance, pain detection systems enable healthcare providers to assess pain more accurately and objectively. As such, these systems result in improved clinical outcomes. This is reflected in the recorded better diagnosis and treatment planning [60]. Another benefit of these systems is that they are particularly valuable for individuals who cannot self-report pain. Such people include elderly patients with dementia, infants, or those with cognitive impairments [61], [62]. Therefore, these automated systems can lead to enhanced care for non-verbal populations. Real-time monitoring and intervention are another great benefit of these pain detection systems. For instance, they allow real-time and continuous monitoring of patients, which decreases the risks of complications. This also facilitates enabling timely interventions in medical emergency cases. In the healthcare environment, this minimizes the burden on healthcare staff. In addition, accurate, real-time, and objective assessment of pain helps caregivers and hospital personnel to quickly determine the right amount of pain medications to give a patient [10, 22, 63, 64, 65].

Healthcare cost reductions are one of the major strengths of pain detection and assessment systems. This is made possible by automating pain assessment, which not only helps reduce the workload on healthcare professionals but also results in cost savings and more efficient resource allocation [3, 66]. Moreover, these pain detection and assessment systems facilitate personalized pain management. This is attained through the tailoring of pain management strategies to individual patients. To facilitate this, patients' unique pain patterns and responses are analyzed [67, 68, 69]. As explained in [70, 71], these automated pain detection and assessment systems have led to advancements in research and technology. By providing large-scale, high-quality data for research and innovation, these systems contribute to the advancement of pain science. It is also possible for automated pain assessment systems to promote equitable access to pain management, particularly in underserved or resource-limited settings. In turn, this can result in improved patient satisfaction, as patients report higher satisfaction when their pain is assessed objectively and managed effectively [72, 73]. Finally, pain detection systems can be integrated with telemedicine platforms to enable remote pain assessment and management [74, 75].

In addition to the above benefits, there are significant advantages of pain recognition and assessment systems when applied in the real world. This is reflected in the provision of results rapidly, improving clinical diagnoses, as well as the provision of continuous monitoring of patients. All these help minimize pressure on the medical team, facilitating decision-making, helping in choosing a treatment plan, and improving the patient experience through continuous interactive support.

## 7. Limitations of current studies

The complexity, subjectivity, and diversity of pain make it extremely difficult to recognize and evaluate. After reviewing the literature on pain recognition and evaluation, some shortcomings and difficulties have been noted in current methods. In this section, we describe such limitations and suggest possible fixes. In addition, future lines of inquiry are given to deal with such issues [76, 77]. The notable limitations are described below.

- **Limited and biased datasets.** Pain expression datasets often lack diversity in age, gender, ethnicity, and medical conditions. This often results in biased models [78].
- **Complexity and variability.** This refers to the intricacy and inconsistency of pain expression since people express pain differently, both facially and behaviorally. This renders it difficult for AI to perform generalization across different individuals [43].
- **Complexity of multimodal data integration.** Amalgamating data from different sources (such as facial expressions, vocalizations, and physiological signals) to create a comprehensive pain assessment is technically challenging and computationally intensive [34].
- **Inconsistent self-reporting.** Patients may under-report or over-report their pain for various reasons. This may be due to psychological factors, fear of medication, or desire for attention. This inconsistency complicates the development of accurate assessment systems [3].
- **Specific populations cannot self-report their pain.** This applies to patients who have dementia, non-verbal expressions, or impaired communications [79].
- **Lack of universally accepted gold standard for automated pain recognition.** Traditional methods such as self-reporting and clinician assessments are often inconsistent and subjective. This makes it difficult to benchmark AI models against reliable ground truth data [3].
- **Difficulty distinguishing pain from other emotions.** Facial expressions and vocal cues related to pain often overlap with different emotions such as stress, anxiety, or fatigue. Differentiating between these states using AI models remains challenging, leading to potential misclassification [80].

To overcome these challenges, there is a need to explore multimodal approaches. This involves the integration of visual, auditory, and physiological data and self-reported pain levels to create more accurate and personalized pain assessment models. Additionally, improving dataset diversity, refining deep learning models, and addressing ethical concerns through transparent AI practices are critical areas for advancement. Addressing these challenges and limitations can advance pain recognition significantly, leading to more accurate, efficient, and personalized pain assessment tools that improve patient care and outcomes.

## 8. Multimodal pain assessment and measurement techniques

Multimodal pain assessment involves using multiple methods or tools to evaluate pain. Pain can be regarded as a subjective and complex experience. Some of the common types of multimodal pain assessment techniques include: self-report measures, behavioral observation, physiological measures, functional imaging, and combined multimodal approaches.

In self-report measures, the patients describe their pain using scales, questionnaires, or verbal descriptions (such as NRS, Visual Analog Scale (VAS), and McGill Pain Questionnaire (MPQ)) [81, 82]. On the other hand, behavioral observation involves monitoring patient behaviors (such as facial expressions and body movements) to assess pain, as shown in Fig. 4. This is mostly applicable in non-verbal patients. Such tools include Pain Assessment IN Advanced Dementia (PAINAD) and FLACC Scale (Legs, Face, Cry, Activity, Consolability) [17, 53, 83]. On its part, physiological measures deploy physiological indicators (such as blood pressure, heart rate, and cortisol levels) to assess pain, as shown in Fig. 5. Such methods include Heart Rate Variability (HRV) and ElectroDermal Activity (EDA) [11, 84]. On the other hand, functional imaging utilizes neuroimaging techniques to observe brain activity associated with pain. Such techniques include functional Magnetic Resonance Imaging (f-MRI) and Positron Emission Tomography (PET) [85]. As shown in Fig. 3, combined multimodal approaches integrate multiple assessment methods (such as self-report, behavioral, and physiological) for a comprehensive evaluation. Such methods include the Multimodal Pain Assessment Tool (MPAT), which helps distinguish and evaluate an integrated picture of pain assessment and management [67, 86, 42].

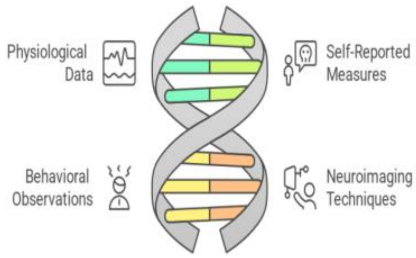


Fig. 3. Integrating diverse data for comprehensive pain assessment

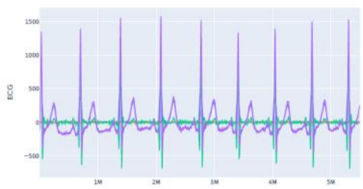


Fig. 4. Automatic pain assessment. "No-pain" and "Pain" states (another example of behavioral signals) [17]


Fig. 5. Result of ECG to assess pain (example of physiological signals) [11]

## 9. Future prospects

Pain management and assessment have been under rapid and innovative developments that should lead to changing pain management, mainly due to technological advances and ongoing research in this domain. Pain management and assessment prospects lie in integrating modern technology with advanced medical research to enable more precise and specialized treatments. These developments are expected to improve patients' quality of life, besides providing comprehensive and integrated healthcare.

AI is a quickly developing new subject that has shown beneficial strengths in numerous facets of healthcare. In order to increase their accuracy and performance over time, the AI models must be built with the ability to continuously learn from and adjust to new data. Numerous recommendations and upcoming projects aim to increase the accuracy of pain evaluation, management, and identification. To facilitate additional pain-related activities (including pain localization and cause recognition), this study recommends that future research should focus on utilizing a variety of pain modalities (including vocal, physiological, facial, and behavioral, among others). To extract the face dynamics for long-term pain scenarios (such as chronic pain), it is important to incorporate the temporal dimension for face expressions. This is because spatiotemporal facial features are more expressive for pain.

The design of an intelligent robot for pain recognition and pain level determination is critical. Therefore, this is an interactive intervention that is not only recent but also an active area of research in the field of robots for pain management. As robots continue to be deployed in new healthcare applications, interest in the field is growing. As such, research into possible pain therapies with robots is still underway. When paired with advanced DL methods, robotics provides a special ability to evaluate multimodal data and offer prompt, precise pain level assessments.

DL models will train social robots to recognize and assess pain in real-time. This will help reduce the burden on healthcare workers as it will allow real-time monitoring. To achieve this, these models will integrate physiological and behavioral data for precise pain assessment. For instance, robots used to detect pain levels typically work using a combination of sensors and AI techniques to analyze data and infer the level of pain based on physiological or behavioral indicators. These indicators include images, video, sounds, and vital signs, among others. This is based on the current sources and reliable scientific research, which show promising potential for developing pain management and assessment approaches in the coming years.

## 10. Discussion and analysis

A comprehensive review of the scientific literature on pain assessment techniques utilizing facial expressions and other physiological indicators (see Table 1) [8, 12, 15, 17-19, 21, 22, 24] revealed that most previous studies have focused on a single data modality. This often involved the use of facial expressions, voice, or gestures in isolation. The reviewed works encompassed ML-based approaches, DL-based approaches, and hybrid methods.

Integrating voice and facial expressions with physiological indicators – such as ECG, GSR, and EMG – enhances the accuracy and efficiency of automated pain assessment systems. Unlike previous studies that have focused on single data channels, this research adopts a multimodal approach, leveraging the unique strengths of each data type to achieve more robust and precise pain assessment outcomes. The significance of this study lies in its potential to advance both the scientific understanding and practical implementation of AI-driven pain detection.

Regarding our results, and in line with prior studies [11, 13, 14, 16, 21-26], it is evident that deep learning models outperform conventional machine learning approaches. This superiority stems from their ability to automatically extract relevant features, classify them with high accuracy, and integrate both feature extraction and classification within a single architecture, trained end-to-end using the backpropagation algorithm. Moreover, advancements in computational power and the availability of large-scale pain databases have enabled these models to deliver stable and highly accurate results. The effectiveness of combining the strengths of deep learning and traditional machine learning is well demonstrated in hybrid models [25, 26]. Our findings indicate that these models perform competitively alongside deep learning-only approaches, underscoring their significant potential for accurate and reliable pain assessment.

A particularly important application emerging from this research is the capability of robotic systems to respond immediately to all types of pain – including acute pain, chronic pain, neuropathic pain, cancer pain, pediatric pain, postoperative pain, musculoskeletal pain, and psychogenic pain [61, 87-91] – thereby opening substantial new opportunities for clinical implementation.

## 11. Conclusion

One of the most important tasks in clinics is the evaluation of pain, particularly severe pain. However, pain evaluation is mainly based on the patient's own descriptions. This presents some challenges for patients with mental illnesses. In addition, this technique cannot be applied to newborns and small children who cannot talk. Fortunately, numerous traits point to discomfort. These include particular alterations in facial expression as well as psychobiological indicators such as heart rate, skin conductance, or skeletal muscle electrical activity. Without the patient's self-report, such data can be utilized to evaluate pain.

This paper has provided the current state-of-the-art in perspectives and research on automatic pain assessment applications in clinical settings. The study emphasizes the significant developments and difficulties in this developing area. This includes automated pain recognition and assessment by the use of multimodal techniques. Compared to unimodal approaches, multimodal systems (which combine data from several sources such as vocal cues, facial expressions, behavioral patterns, and physiological signals) have shown better robustness and accuracy in pain detection. These systems incorporate the strengths of numerous techniques, such as DL, computer vision, and ML. This study has also shown that robotics technologies and natural languages offer a more complete and objective evaluation of pain. This helps in addressing the constraints of conventional self-reporting approaches. However, in clinical environments where patient care depends on precise pain evaluation, multimodal techniques are the most suitable. This survey has shown that automated multimodal pain evaluation offers more individualized and timely interventions for patients in need. It greatly helps in transforming pain management, particularly for patients who cannot communicate verbally. In spite of these major contributions, there are still some major obstacles to general acceptance. Some of these challenges include data heterogeneity, privacy issues, and the requirement for annotated, large datasets. In addition, interpretability regarding AI-driven models and their generalizability among several demographics and pain disorders is another challenge that needs to be addressed. Future directions in this domain will involve the creation of more effective data fusion methods, enhancing real-time processing capacity, and guaranteeing ethical data use practices. In addition, there is a need for scalable, reliable, and easily available pain recognition systems that can easily facilitate cooperation among various stakeholders, such as technologists, doctors, and researchers.

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