South Asian Journal of Engineering and Technology Research Article

Open Access Full Text Article 123(2022) 43-53 DOI: 10.26524/sajet.2022.12.37

Automatic Pain Recognition Techniques: A State-of-the-art Review

Patil Manisha Shanataram

Department of Computer Engineering(Assistant Professor)SSVPS B S D College of Engneering(DBATU Lonere) Dhule, India

Patil Hitendra Dhansing

Department of Computer Engineering(Professor)SSVPS B S D College of Engneering(DBATU Lonere)Dhule, India

Corresponding author.
Correspondence: **Patil Manisha Shanataram**
E-mail: patmanisha@gmail.com

Article info
Received 28 th February 2022 Received in revised form 3 April 2022 Accepted 4 July 2022

Keywords
Pain, recognition, feature, classification

Abstract
Pain is a dynamic and subjective experience that can be difficult to measure. Automated clinical pain assessment method offers a lot of potential, and they're not widely employed in medical practice presently. There is now an a need for a comprehensive and precise method to identify acute pain among intensive care units in order to assist professionals in dispensing pain relievers at the proper dosage and on time. We review and discuss autonomous pain identification algorithms in this article also provide an introduction of pain processes and reactions, as well as a discussion of commonly used clinical pain assessment techniques and shared datasets.

I. INTRODUCTION

Pain is a dynamic occurrence that has been still not clearlyrealized. The standard statement of pain is “a stressful associated with emotions response generated by probable muscle injury, or characterized in relations of certain destruction"[48]. Basic research, on the other hand, continuesto advance scientific knowledge of pain, and there is an active discussion about changing the definition [49-50]. Such kind of pain, known as acute pain, supports in the identification of potentially hazardous situations, the prevention of tissue damage, and the facilitation of recovery by preventing behaviours which may cause further tissue damage [50]. Many humans, as well as community overall, are affected by pain. The growing demand for pain treatment has been aided by advances in medicine: Many people now a days are suffering diseases that were formerly deadly, such as HIV, cancer, and cardiovascular disease. However, they will have chronic pain as a result of either the existing disease or the surgery or even after the sickness has been cleared, by neurological damage caused by the condition [52]. Chemotherapy, Surgery, and radiotherapy are all common treatments that inflict pain [31]. Persistent pain has serious consequences for the person in pain, as well as her friends andfamily members.

Scientifically valid pain assessment is needed fordiagnostic process, selecting a suitable treatment, evaluating progress, and deciding whether such a treatment should be maintained or improved. So that, assessing and managing pain is important besides for providing relief. But also for eliminating together instantaneous and lasting implication as decreases life eminence however, it also completely undermines the neurological system [41]. Unrelieved pain can rise to chronic pain condition, which also is marked by restricted movement, weakened immunity, difficulty concentrating, obesity, and sleep disturbances. However, incorrect therapy might cause complications and complications for patients.

Although advances in technology and knowledge, pain is still mismanaged [52-54], [69]. However this is a prevalent difficult, it disproportionally disturbs patients with weak message skills, that are unable to communicate overall pain perception and those who's express has low ecological validity. In the next decade, autonomous pain assessment systems based on pain behaviours will be developed (video facial terminologies, movements of body and vocalizations) and Physiological responses would be used to enhance current pain diagnostic tools in order to achieve better pain treatment. In comparison to conventional assessment methods, it might regularly monitor pain. This could lead to improved treatment outcomes, such as besides facilitating early diagnosis for patients being unable to request assistance on their own. Moreover, automatic structures will be much more accurate rather than a person observer, whom assessment will beaffected with different aspects like as the patient's appearanceor relationship to the patient [53, 55, 69, 72, 73].

II. PAIN MECHANISMS AND RESPONSES

Pain is a unique, individual, sensory experience that originates in the brain. Pain is more than just a physical sensation [56]. The pain feeling should be identified from thecause of the pain (such as muscle destruction caused by nerve injury), the pain reaction (vocal communication and non- verbal Indicators) and pain assessment. The cause of pain is usually identifiable, and it can be managed by intentional painstimulus.

A. *Biological Mechanisms*

The pain method involves numerous aspects of the neurological structure. The development usually starts with unpleasant mechanical, chemical cold, heat, or inflammatory stimuli activating sensory nerve cells. These signals stimulate nociceptors, which become primary sensory neurons with noxious stimuli-detecting specific receptors. The inducedelectrical impulses are transmitted to the spinal cord throughnociceptive fibers. Excitatory network and also inhibitory interneuron network in the spinal cord can be stimulated, resulting in a protective reflexive retraction response. The perceptual exclusionary experience of pain is the resultant ofnext processing of nociceptive information in several spinal organs. Whereas a nociceptive signal usually causes pain, numerous factors can influence this response.

B. *Biological Responses*

Connections among neural network are complex, involved in Pain perceptions and autonomic control [57] because an increase in sympathetic outflow, leading in modifications in physiological signals that can be measurable [58].

Skin conductance is a signal [59] that changes in responseto pain and is automatically modulated. Even though sweat organs are just stimulated by sympathetic excitatory sensoryneurons [57], increased sympathetic flow in pain response leads sweat to be released into apertures on the surface of skin [59]. Heat influences the electrical performance of the skin (electrodermal, EDA and electrodermal activity), enhancing electrode potential until underarm sweat is evaporated or reabsorbed, sympathetic nervous system excitation also creates significant cardiovascular consequences. It has an influence on the heart rate [60], this induces tachycardia and heart rate irregularity, an indicator of autonomic heart rate control. Especially, Pain massively increases differentfrequencies power, as evaluated by energy power spectrum. Moreover, Peripheral vascular resistance and stroke volume also are boosted by pain.

C. *Behavioral Responses*

Facial expressions, gestures, and speech patterns are characteristics of behavioural pain reactions. Chronic pain typically results in significant changes in daily behaviour andpublic communication. Presently, various pain-related facial terms that happen comparatively constantly across a wide variety of laboratory pain situations and evaluation pain methods [61]. Consequently, the intensity of facial movement's increases as the strength of painful stimuli increases [62]. The majority of pain-related bodily motions help to defend against future harm and to relieve unpleasantness. Pain behaviour also includes paralinguistic vocalisations (laughing, groaning, and moaning) and sound quality features including loudness, and insecurity detected throughout voiced report [61].

D. Emotion and Pain

Pain is classified as either a sensory or also an emotional reaction. It has an emotive element that covers a wide range of feelings, the majority of which are destructive and connected to the discomfort to potential consequences. Aggression and sorrow also performance key roles,particularly in chronic pain [62]. Lastly, physiological and behavioural responses indications and their groupings, the issue of whether pain can be consistently and objectively separated from its associated emotions remains unresolved.

III. TOOLS FOR PAIN ASSESSMENT IN CLINICAL APPLICATION

In clinical practice, pain is typically based mainly on the patient's report intensity and variables that relieve and increase the pain. Self-reporting is the explicit presentation of pain associated information through a person in pain, generally through verbal or gestures such as directing to an illustration that signifies their feelings in answer to a request. Patient care regulations underline that report is the utmost reliable method of measuring pain if the person is able to speak [63-69].

IV. DATASETS

The best frequently used database is the BioVid Heat Pain Database [35]. It was acquired through a partnership between the University of Magdeburg's Neuro-Information groups. Total 90 patients were submitted to four intensities of experimentally induced heat sensitivity. Table 1 represents the properties of publicly accessible datasets for pain recognitionresearch.

V. METHODOLOGIES OF PAIN RECOGNITION

We directed an efficient literature search, as described in introduction, to evaluate the existing automated pain recognition approaches. In the next subsections, we explore the recognition input systems and the system processingtechniques.

A. Modalities and Sensors

Pain assessment needs at minimum single sensor information stream to share information to the machine. A medium of this type is sometimes referred to as a modality. The most significant pain recognition modalities may beclassified into two parts: behaviour and physiology. Face expression; body motions like rubbing, guarding, and skull movements; vocalisations and vocal arguments that can be shared by communication and may contain self-report information are all examples of behavioural modalities. In thephysiology area, brain action, cardiac action are all of interest. A uni-modal system consist of only one modality; a multimodal approach takes input from multiple modalities.

1) Camera-Based Methodology: To date, the large majority of pain detection systems have relied at camera imagery with facial expressions. The majority of existing pain recognition research focused on Facial expression modality. In general, cameras have a narrow range of view, thus understanding images is much more complicated than processing other instrument inputs. Cameras, on the other hand, are non-contact devices that may be more comfortable or patients and more efficient for healthcare workers thancontact-based sensors [42].

2) Contact-Sensor Techniques: The direct interaction sensors EDA and ECG have been the second-most extensively utilised. Since, the introduction of the BioVid database, followed by sEMG of the trapezius muscle-Sensor techniques. Pain was identified using a variety of physiological indicators acquired from electronic flow spreadsheets in institutions. EDA consistently outperforms the only one modalities that have evaluated [25], [33].

TABLE I. Databases for Pain Recognition that are available to the public for research

Database	Subjects	Stimuli	Data Modalities (D)
BioVid Heat Pain[30], [66], [67]	Total 90 adul tparticipants	14k heat pain (20 repetitions 4 intensities2parts 90 adult patient)	Video signal, biomedical indicators
BP4D-Spontaneous [64]	Total 41 adults	emotion elicitation, 41 cold pressor task	Color and 3D video of face
BP4D+ [68]	Total 140 adults	emotion elicitation ,140 cold pressor task	Face of color video 3D and thermal,medical signal such as respiration rate, blood pressure, heart rate andEDA
UNBC McMaster Shoulder Pain [65]	Total 25 patients shoulder pain	Total 200 video signal,	Face video such as low resolution,social interaction and talking
MIntPAI N[41]	Total 20 adults	40 stimuli in 4 intensities of 2 trials and20 participant of 2k electrical pain	Fave video of color, thermal anddepth

TABLE II. Bio-Vid Database has been used to evaluate Pain Recognition systems

Author	Feature	Classification Model
M. Amirian et al.[71]	Descriptor with time series statics signal.	Radial Basis Function networks,
S. Gruss et al.[72]	159 features based on statistical analyses	radial basis function kernel andSVM
M. Kachele et al. [22]	Head pose, peak height and difference, B.W. and entropy.	SVM and Random forest
M. Kachele et al. [23]	Physiological signal and geometric-based andappearance-based from video.	Random Forest (RF)
M. Kachele et al.[24]	Mean and the standard deviation from EMG.	KNN and Random forest
M. Kachele et al. [25]	frame level, skewness, spectral entropy, entropy anddensity	Random Forest
Lopez-M. 17 [26]	calculated the Skin conductance (SC) andElectrocardiogram (ECG) features	multi-task neural network(MT-NN)
Lopez-M.18 [27]	Mean, max, range, AUC	Recurrent neural network-based regression algorithm
Walter 14 [28]	Shannon entropy, and heart rate	Decision Trees, K-NN, and SVMs.
Walter 15 [29]	Features based on signal amplitude and frequency also based on entropy, stationary and statistical moments.statistical parameters from video signal	KNN and Random forest

Werner 14 [31]	Features of amplitude from (GSR) ,frequency featuresfrom (EMG) at trapezius muscle and three heart rate variability features from (ECG)	Random Forest
Werner 17 [32]	measure facial activity and expressiveness	Random Forest
Yang 16 [18]	texture information form face	Support Vector Machine(SVM)
F. Pouromran [70]	22 features capture properties such as linear and nonlinearautocorrelation, successive differences.	Support Vector Regressor, XGBoost, KNN, Neural Networks

B. Features and Models

The raw data is analysed for patterns that can be used to predict a pain state in the person being studied. Features are collected from the input signal, which are a more exclusionary and generally lesser dimensional representation. There are an amount of diverse kinds of features classified as (1) learned features, (2) generic features, (3) hand-designed. Generic features are useful in other domains, but pain recognition they not provide better result. Such as, LBP image features. Hand- crafted features are constructed for a specific objective through dedicated knowledge; they are generally simple to interpret and low-dimensional. Another feature such as use during the training procedure, the extracted features is optimized for the specific task termed as learned features. These are typically higher dimensionality and hard to interpret.

1) Face Expression Features: Feature extraction is a process in the processing system during camera-based facial pain expression analysis. It might include 1) identifying facial characteristics (points around the mouth, brows and eyes and among others) 2) To improvement invariance to translatio*n, scaling, and rotation, utiliz*e facial texture. A range of frame- based features have utilized to pain recognise [1], [8], [11], [15-16], [19], [20], [35]; simplest pixel representations represent illustrations using generic appearance features [3], [21], [37], LBP [8], [12], [16], [18], [20], [35], HOG [1], [6], [12], [34], Discrete Cosine Transform (DCT) [35], Gabor [9], [12], [20], [39], [44], Scale Invariant Feature Transform(SIFT) [10], [14], neural network-learned features [7], [13], [17], [21], [41].

2) Physiological Features: All other sensor signals, apartfrom camera images and neuroimaging, are interpreted as time signal. In the evaluation of sEMG, EDA signals, we identify numerous variations of Time series signal Descriptors (TSD). Walter [48] investigated the effectiveness of amplitude, variability, and frequency. sEMG (corrugator, zygomaticus muscle and trapezius) and stationarity, EDA frequency, entropy, linearity and, entropy features for pain recognition. Based on physiological objectives, EDA has divided into two aspects while retrieving information from both components independently [23], [25], [28], [33].

3) Recognition Models: After feature extraction, the framework that relates the features to the implicit pain status is the second essential processing component. The model may also include data fusion, especially for system integration in a multimodal system, which can be done at thedecision, feature, or intermediate levels. The most of methodsutilise Support Vector Machines (SVMs) to categorise pain, either linearly or with a Radial Basis Function (RBF) kernel [11], [28], [30], [38], [39], [42]. Relevance Vector Regression generates continuous-valued output [1], [5].and related Support Vector Regression [2], [4], [16], [20] models. Random Forests are another popular model (RF) [29], [32], [35, [36], [41] variations of Conditional Random Fields (CRF) [3], [8], [15], Nearest Neighbor (NN) classifiers [6], [19], [24], [36], [37], and various neural networks. Convolutional Neural Networks are one of the CNN architectures utilised for pain identification [13], [17], [21], [41], Radial Basis Function (RBF) networks [25], Long Short-Term Memory (LSTM) networks [8], [13], [41], Data fusion is a process of integrating various modalities, features,judgement score, or even other information sources to createa single final prediction [22], [23], [25], [33].

C. Ground Truth

Different objectives being explored by the evaluated automated pain assessment systems. The most common are evaluating the existence of pain (a binary classification) and assessing the intensity of pain. Such systems require adequateground truth for development and evaluation. The majority ofother study employed the provided stimulus as ground truth, either with [46], [47] or instead of customized assessment [39], [40], [43]. The most of these studies aim to investigate the occurrence of pain or anticipate the intensity of symptomsin separate categories [40],[41], [45], The later researches revealed that an integrated computer vision system outperformed skilled human observers in identifying realisticfrom manufactured pain signals on the face.

VI. CONCLUSION

Health services are complicated processes which include interaction among people, organizations, and equipment. Researcher kept in mind these information as an initial phase to design an intelligent health-care system. This article provides a complete overview of pain assessment techniquesthat depend on several machine learning techniques. The dadaset utilized for pain assessment was consider as video or imagebased facial expression or biomedical signal.

REFERENCES

1. Egede, Joy, Michel Valstar, and Brais Martinez. "Fusing Deep Learned and Hand-Crafted Features of Appearance, Shape, and Dynamics for Automatic Pain Estimation." *2017 12th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2017)*, 2017. https://doi.org/10.1109/fg.2017.87
2. Florea, Corneliu, Laura Florea, Raluca Butnaru, Alessandra Bandrabur, and Constantin Vertan. "PainIntensity Estimation by a Self-Taught Selection of Histograms of Topographical Features." *Image and Vision Computing* 56 (2016): 13–27. https://doi.org/10.1016/j.imavis.2016.08.014.
3. Ghasemi, Afsane, Xinyu Wei, Patrick Lucey, Sridha Sridharan, and Clinton Fookes. "Social Signal Processing for Pain Monitoring Using a Hidden Conditional Random Field." *2014 IEEE Workshop on Statistical Signal Processing (SSP)*, 2014. https://doi.org/10.1109/ssp.2014.6884575.
4. Hong, Xiaopeng, Guoying Zhao, Stefanos Zafeiriou,Maja Pantic, and Matti Pietikäinen. "Capturing Correlations of Local Features for Image Representation." *Neurocomputing* 184 (2016): 99–106. https://doi.org/10.1016/j.neucom.2015.07.134.
5. Kaltwang, Sebastian, Sinisa Todorovic, and Maja Pantic. "Doubly Sparse Relevance Vector Machine for Continuous Facial Behavior Estimation." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 38, no. 9 (2016): 1748–61. https://doi.org/10.1109/tpami.2015.2501824.
6. Khan, Rizwan Ahmed, Alexandre Meyer, Hubert Konik,and Saida Bouakaz. "Pain Detection through Shape and Appearance Features." *2013 IEEE International Conference on Multimedia and Expo (ICME)*, 2013. https://doi.org/10.1109/icme.2013.6607608.
7. Kharghanian, Reza, Ali Peiravi, and Farshad Moradi. "Pain Detection from Facial Images Using Unsupervised Feature Learning Approach." *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2016. https://doi.org/10.1109/embc.2016.7590729.
8. Martinez, Daniel Lopez, Ognjen Rudovic, and Rosalind Picard. "Personalized Automatic Estimation of Self-Reported Pain Intensity from Facial Expressions." *2017IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, 2017.
9. https://doi.org/10.1109/cvprw.2017.286.

10. Lo Presti, Liliana, and Marco La Cascia. "Boosting Hankel Matrices for Face Emotion Recognition and Pain Detection." *Computer Vision and Image Understanding*156(2017):19–33. https://doi.org/10.1016/j.cviu.2016.10.007.
11. Neshov, Nikolay, and Agata Manolova. "Pain Detection from Facial Characteristics Using Supervised Descent Method." 2015 IEEE 8th International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (IDAACS), 2015. https://doi.org/10.1109/idaacs.2015.7340738.
12. Rathee, Neeru, and Dinesh Ganotra. "A Novel Approach for Pain Intensity Detection Based on Facial Feature Deformations." *Journal of Visual Communication and Image Representation* 33 (2015): 247–54. https://doi.org/10.1016/j.jvcir.2015.09.007.
13. Rathee, Neeru, and Dinesh Ganotra. "Multiview Distance Metric Learning on Facial Feature Descriptors for Automatic Pain Intensity Detection." *Computer Vision and Image Understanding* 147 (2016): 77–86. https://doi.org/10.1016/j.cviu.2015.12.004.
14. Rodriguez, Pau, Guillem Cucurull, Jordi Gonalez, Josep
15. M. Gonfaus, Kamal Nasrollahi, Thomas B. Moeslund, and F. Xavier Roca. "Deep Pain: Exploiting Long Short-Term Memory Networks for Facial Expression Classification." *IEEE Transactions on Cybernetics*, 2017, 1–11. https://doi.org/10.1109/tcyb.2017.2662199.
16. Rudovic, Ognjen, Vladimir Pavlovic, and Maja Pantic. "Context-Sensitive Dynamic Ordinal Regression for Intensity Estimation of Facial Action Units." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 37, no. 5 (2015): 944–58. https://doi.org/10.1109/tpami.2014.2356192.
17. Ruiz, Adria, Xavier Binefa, and Joost Van de Weijer. "Regularized Multi-Concept Mil for Weakly-Supervised Facial Behavior Categorization." *Proceedings of the British Machine Vision Conference 2014*, 2014. https://doi.org/10.5244/c.28.13.
18. Rupenga, Moses, and Hima B. Vadapalli. "Automatic Spontaneous Pain Recognition Using Supervised Classification Learning Algorithms." *2016 Pattern Recognition Association of South Africa and Robotics and Mechatronics International Conference (PRASA-RobMech)*, 2016.
19. https://doi.org/10.1109/robomech.2016.7813150.
20. Wang, Feng, Xiang Xiang, Chang Liu, Trac D. Tran, Austin Reiter, Gregory D. Hager, Harry Quon, Jian Cheng, and Alan L. Yuille. "Regularizing Face Verification Nets for Pain Intensity Regression." *2017 IEEE International Conference on Image Processing(ICIP),*2017. https://doi.org/10.1109/icip.2017.8296449.
21. Yang, Ruijing, Shujun Tong, Miguel Bordallo, Elhocine Boutellaa, Jinye Peng, Xiaoyi Feng, and Abdenour Hadid. "On Pain Assessment from Facial Videos Using Spatio-Temporal Local Descriptors." *2016 Sixth International Conference on Image Processing Theory, Tools and Applications (IPTA)*, 2016.
22. https://doi.org/10.1109/ipta.2016.7820930.
23. Zafar, Zuhair, and Nadeem Ahmad Khan. "Pain Intensity Evaluation through Facial Action Units." *2014 22nd International Conference on Pattern Recognition*, 2014.https://doi.org/10.1109/icpr.2014.803.
24. Zhao, Rui, Quan Gan, Shangfei Wang, and Qiang Ji. "Facial Expression Intensity Estimation Using Ordinal Information." *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016.
25. https://doi.org/10.1109/cvpr.2016.377.
26. Zhou, Jing, Xiaopeng Hong, Fei Su, and Guoying Zhao. "Recurrent Convolutional Neural Network Regression for Continuous Pain Intensity Estimation in Video." *2016 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, 2016.
27. https://doi.org/10.1109/cvprw.2016.191.
28. Kächele, Markus, Philipp Werner, Ayoub Al-Hamadi, Günther Palm, Steffen Walter, and Friedhelm Schwenker. "Bio-Visual Fusion for Person-IndependentRecognition of Pain Intensity." *Multiple Classifier Systems*, 2015, 220–30. https://doi.org/10.1007/978-3- 319-20248-8_19.

29. Kächele, Markus, Patrick Thiam, Mohammadreza Amirian, Philipp Werner, Steffen Walter, Friedhelm Schwenker, and Günther Palm. "Multimodal Data Fusion for Person-Independent, Continuous Estimation of Pain Intensity." *Engineering Applications of Neural Networks*, 2015, 275–85. https://doi.org/10.1007/978-3-319-23983-5_26.
30. Kachele, Markus, Patrick Thiam, Mohammadreza Amirian, Friedhelm Schwenker, and Gunther Palm. "Methods for Person-Centered Continuous Pain Intensity Assessment from Bio-Physiological Channels." *IEEE Journal of Selected Topics in Signal Processing* 10, no. 5 (2016): 854–64.https://doi.org/10.1109/jstsp.2016.2535962.
31. Kächele, Markus, Mohammadreza Amirian, Patrick Thiam, Philipp Werner, Steffen Walter, Günther Palm, and Friedhelm Schwenker. "Adaptive Confidence Learning for the Personalization of Pain Intensity Estimation Systems." *Evolving Systems* 8, no. 1 (2016): 71–83. https://doi.org/10.1007/s12530-016-9158-4.
32. Lopez-Martinez, Daniel, Ognjen Rudovic, and Rosalind Picard. "Physiological and Behavioral Profiling for Nociceptive Pain Estimation Using Personalized Multitask Learning." arXiv.org, November 10, 2017. https://arxiv.org/abs/1711.04036.
33. Lopez-Martinez, Daniel, and Rosalind Picard. "Continuous Pain Intensity Estimation from Autonomic Signals with Recurrent Neural Networks." *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2018. https://doi.org/10.1109/embc.2018.8513575.
34. Walter, Steffen, Sascha Gruss, Kerstin Limbrecht- Ecklundt, Harald C. Traue, Philipp Werner, Ayoub Al-Hamadi, Nicolai Diniz, Gustavo Moreira da Silva, and Adriano O. Andrade. "Automatic Pain Quantification Using Autonomic Parameters." *Psychology & Neuroscience* 7, no. 3 (2014): 363–80. https://doi.org/10.3922/j.psns.2014.041.
35. Walter, Steffen, Sascha Gruss, Markus Kächele, Friedhelm Schwenker, philipp Werner, Ayoub Al- Hamadi, Adriano Andrade, Gustavo Moreira, and Harald Traue. "Data Fusion for Automated Pain Recognition." *Proceedings of the 9th International Conference on Pervasive Computing Technologies for Healthcare*,2015.https://doi.org/10.4108/icst.pervasivehealth.2015. 259166.
36. Werner, Philipp, Ayoub Al-Hamadi, Robert Niese, Steffen Walter, Sascha Gruss, and Harald Traue."Towards Pain Monitoring: Facial Expression, Head Pose, a New Database, an Automatic System and Remaining Challenges." *Procedings of the British Machine Vision Conference 2013*, 2013. https://doi.org/10.5244/c.27.119.
37. Werner, Philipp, Ayoub Al-Hamadi, Robert Niese, Steffen Walter, Sascha Gruss, and Harald C. Traue. "Automatic Pain Recognition from Video and Biomedical Signals." *2014 22nd InternationalConference on Pattern Recognition*, 2014. https://doi.org/10.1109/icpr.2014.784.
38. Werner, Philipp, Ayoub Al-Hamadi, and Steffen Walter. "Analysis of Facial Expressiveness during Experimentally Induced Heat Pain." *2017 Seventh International Conference on Affective Computing and Intelligent Interaction Workshops and Demos (ACIIW)*, 2017. https://doi.org/10.1109/aciiw.2017.8272610.
39. Thiam, Patrick, and Friedhelm Schwenker. "Multi- Modal Data Fusion for Pain Intensity Assessment and Classification." *2017 Seventh International Conference on Image Processing Theory, Tools and Applications (IPTA)*, 2017.https://doi.org/10.1109/ipta.2017.8310115.
40. Thiam, Patrick, Viktor Kessler and Friedhelm Schwenker. "Hierarchical Combination of Video Features for Personalised Pain Level Recognition." *ESANN* (2017).
41. Aung, Min S., Sebastian Kaltwang, Bernardino Romera-Paredes, Brais Martinez, Aneesha Singh, Matteo Cella, Michel Valstar, et al. "The Automatic Detection of Chronic Pain-Related Expression: Requirements, Challenges and the Multimodal Emopain Dataset." *IEEE Transactions on Affective Computing* 7, no. 4 (2016): 435–51. https://doi.org/10.1109/taffc.2015.2462830.
42. Zamzmi, Ghada, Chih-Yun Pai, Dmitry Goldgof, Rangachar Kasturi, Yu Sun, and Terri Ashmeade.

"Automated Pain Assessment in Neonates." *Image Analysis*, 2017, 350–61. https://doi.org/10.1007/978-3- 319-59129-2_30.

43. Adibuzzaman, Mohammad, Colin Ostberg, Sheikh Ahamed, Richard Povinelli, Bhagwant Sindhu, Richard Love, Ferdaus Kawsar, and Golam Mushih Ahsan. "Assessment of Pain Using Facial Pictures Taken with a Smartphone." *2015 IEEE 39th Annual Computer Software and Applications Conference*, 2015.
44. https://doi.org/10.1109/compsac.2015.150.
45. Ashouri, Sajad, Mohsen Abedi, Masoud Abdollahi, Farideh Dehghan Manshadi, Mohamad Parnianpour, and Kinda Khalaf. "A Novel Approach to Spinal 3-D Kinematic Assessment Using Inertial Sensors: Towards Effective Quantitative Evaluation of Low Back Pain in Clinical Settings." *Computers in Biology and Medicine* 89 (2017): 144–49.
46. https://doi.org/10.1016/j.compbiomed.2017.08.002.
47. Bartlett, Marian Stewart, Gwen C. Littlewort, Mark G. Frank, and Kang Lee. "Automatic Decoding of Facial Movements Reveals Deceptive Pain Expressions." *Current Biology* 24, no. 7 (2014): 738–43. https://doi.org/10.1016/j.cub.2014.02.009.
48. Chu†, Yaqi, Xingang Zhao, Jun Yao†, Yiwen Zhao, and Zhenwei Wu. "Physiological Signals Based Quantitative Evaluation Method of the Pain." *IFAC Proceedings Volumes* 47, no. 3 (2014): 2981–86. https://doi.org/10.3182/20140824-6-za-1003.01420.
49. Haque, Mohammad A., Ruben B. Bautista, Fatemeh Noroozi, Kaustubh Kulkarni, Christian B. Laursen, Ramin Irani, Marco Bellantonio, et al. "Deep Multimodal Pain Recognition: A Database and Comparison of Spatio-Temporal Visual Modalities." *2018 13th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2018)*, 2018. https://doi.org/10.1109/fg.2018.00044.
50. Oshrat, Yaniv, Ayala Bloch, Anat Lerner, Azaria Cohen, Mireille Avigal, and Gabi Zeilig. "Speech Prosody as a Biosignal for Physical Pain Detection." *Speech Prosody2016*, 2016.
51. https://doi.org/10.21437/speechprosody.2016-86.
52. Pourshoghi, Ahmad, Issa Zakeri, and Kambiz Pourrezaei. "Application of Functional Data Analysis in Classification and Clustering of Functional near-Infrared Spectroscopy Signal in Response to Noxious Stimuli." *Journal of Biomedical Optics* 21, no. 10 (2016): 101411.https://doi.org/10.1117/1.jbo.21.10.101411.
53. Susam, Busra T., Murat Akcakaya, Hooman Nezamfar, Damaris Diaz, Xiaojing Xu, Virginia R. de Sa, Kenneth
54. Craig, Jeannie S. Huang, and Matthew S. Goodwin. "Automated Pain Assessment Using Electrodermal Activity Data and Machine Learning." *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2018.
55. https://doi.org/10.1109/embc.2018.8512389.
56. Vatankhah, Maryam, and Amir Toliyat. "Pain Level Measurement Using Discrete Wavelet Transform." *International Journal of Engineering and Technology* 8,no. 5 (2016): 380–84. https://doi.org/10.7763/ijet.2016.v8.917.
57. Wang, Shuang, Xiaoqian Jiang, Zhanglong Ji, Robert El- Kareh, Jeeyae Choi, and Hyeoneui Kim. "When You Can't Tell When It Hurts: A Preliminary Algorithm to Assess Pain in Patients Who Can't Communicate."AMIA ... Annual Symposium proceedings. AMIA Symposium. American Medical Informatics Association, November 16, 2013.
58. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC39001 56/.
59. Werner, Philipp, Ayoub al-Hamadi, and Robert Niese. "Comparative Learning Applied to Intensity Rating of Facial Expressions of Pain." *International Journal of Pattern Recognition and Artificial Intelligence* 28, no. 05 (2014): 1451008.

60. https://doi.org/10.1142/s0218001414510082.
61. Williams, Amanda C., and Kenneth D. Craig. "Updating the Definition of Pain." *Pain* 157, no. 11 (2016): 2420–23. https://doi.org/10.1097/j.pain.0000000000000613.
62. Aydede, Murat. "Defending the IASP Definition of Pain." *The Monist* 100, no. 4 (2017): 439–64. https://doi.org/10.1093/monist/onx021.
63. AC, Williams. "Facial Expression of Pain: An Evolutionary Account." *The Behavioral and brain sciences*. 25,no.4(2002):439-55.. doi:10.1017/s0140525x02000080. PMID: 12879700.
64. Mäntyselkä, Pekka, Esko Kumpusalo, Riitta Ahonen, Anne Kumpusalo, Jussi Kauhanen, Heimo Viinamäki, Pirjo Halonen, and Jorma Takala. "Pain as a Reason to Visit the Doctor: A Study in Finnish Primary Health Care." *Pain* 89, no. 2 (2001): 175–80. https://doi.org/10.1016/s0304-3959(00)00361-4.
65. Turk, D. C., & Melzack, R. (2011). The measurement ofpain and the assessment of people experiencing pain. In
66. C. Turk & R. Melzack (Eds.), *Handbook of pain assessment* (pp. 3–16). The Guilford Press
67. Beck SL;Dunton N;Berry PH;Brant JM;Guo JW;Potter C;Spornitz B;Eaton J;Wong B; "Dissemination and Implementation of Patient-Centered Indicators of Pain Care Quality and Outcomes." Medical care. U.S. National Library of Medicine, 2018.
68. https://pubmed.ncbi.nlm.nih.gov/30570589/.
69. Herr, Keela, Patrick J. Coyne, Margo McCaffery, Renee Manworren, and Sandra Merkel. "Pain Assessment in the Patient Unable to Self-Report: Position Statement with Clinical Practice Recommendations." *Pain Management Nursing* 12, no. 4 (2011): 230–50.https://doi.org/10.1016/j.pmn.2011.10.002.
70. Zamzmi, Ghada, Rangachar Kasturi, Dmitry Goldgof, Ruicong Zhi, Terri Ashmeade, and Yu Sun. "A Review of Automated Pain Assessment in Infants: Features, Classification Tasks, and Databases." *IEEE Reviews in Biomedical Engineering* 11 (2018): 77–96. https://doi.org/10.1109/rbme.2017.2777907. Prkachin, Kenneth M., and Kenneth D. Craig. "Expressing Pain: The Communication and Interpretation of Facial Pain Signals." *Journal of Nonverbal Behavior* 19, no. 4 (1995): 191–205. https://doi.org/10.1007/bf02173080.
71. Stewart, Gordon, and Ajit Panickar. "Role of the Sympathetic Nervous System in Pain." *Anaesthesia & Intensive Care Medicine* 14, no. 12 (2013): 524–27.https://doi.org/10.1016/j.mpaic.2013.09.003.
72. Boucsein, Wolfram. "Electrodermal Activity." *SpringerScience & Business Media*, 2012.
73. https://doi.org/10.1007/978-1-4614-1126-0.
74. Benedek, Mathias, and Christian Kaernbach. "Decomposition of Skin Conductance Data by Means of Nonnegative Deconvolution." *Psychophysiology* 47, no. 647-658 (2010). https://doi.org/10.1111/j.1469-8986.2009.00972.x.
75. Appelhans, Bradley, and Linda Luecken. "Heart Rate Variability and Pain: Associations of Two Interrelated Homeostatic Processes." *Biological Psychology* 77, no. 2 (2008) :174–82. https://doi.org/10.1016/j.biopsycho.2007.10.004.
76. Prkachin, Kenneth M., and Patricia E. Solomon. "The Structure, Reliability and Validity of Pain Expression: Evidence from Patients with Shoulder Pain." *Pain* 139, no.2 (2008): 267–74. https://doi.org/10.1016/j.pain.2008.04.010.
77. Simon, Daniela, Kenneth D. Craig, Frederic Gosselin, Pascal Belin, and Pierre Rainville. "Recognition and Discrimination of Prototypical Dynamic Expressions of Pain and Emotions." *Pain* 135, no. 1 (2008): 55–64. https://doi.org/10.1016/j.pain.2007.05.008.
78. Lumley, Mark A., Jay L. Cohen, George S. Borszcz, Annmarie Cano, Alison M. Radcliffe, Laura S. Porter, Howard Schubiner, and Francis J. Keefe. "Pain and Emotion: A Biopsychosocial Review of Recent Research." *Journal of Clinical Psychology* 67, no. 9(2011): 942–68. https://doi.org/10.1002/jclp.20816.

79. Puntillo, Kathleen A., Ann B. Morris, Carol L. Thompson, Julie Stanik-Hutt, Cheri A. White, and Lorie
80. R. Wild. "Pain Behaviors Observed during Six Common Procedures: Results from Thunder Project II*." *Critical Care Medicine* 32, no. 2 (2004): 421–27.https://doi.org/10.1097/01.ccm.0000108875 35298.d2.
81. Kunz, M., and S. Lautenbacher. "The Faces of Pain: A Cluster Analysis of Individual Differences in Facial Activity Patterns of Pain." *European Journal of Pain* 18, no. 6 (2013): 813–23. https://doi.org/10.1002/j.1532-2149.2013.00421.x.
82. Zhang, Lin, Steffen Walter, Xueyao Ma, Philipp Werner, Ayoub Al-Hamadi, Harald C. Traue, and Sascha Gruss. "'BioVid Emo DB': A Multimodal Database forEmotion Analyses Validated by Subjective Ratings." *2016 IEEE Symposium Series on Computational Intelligence (SSCI),* 2016.
83. https://doi.org/10.1109/ssci.2016.7849931.
84. Zhang, Zheng, Jeffrey M. Girard, Yue Wu, Xing Zhang, Peng Liu, Umur Ciftci, Shaun Canavan, et al. "Multimodal Spontaneous Emotion Corpus for Human Behavior Analysis." *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016. https://doi.org/10.1109/cvpr.2016.374,
85. Brahnam, Sheryl, Chao-Fa Chuang, Frank Y. Shih, and Melinda R. Slack. "SVM Classification of Neonatal Facial Images of Pain." *Fuzzy Logic and Applications*, 2006, 121–28. https://doi.org/10.1007/11676935_15,
86. Gruss, Sascha, Mattis Geiger, Philipp Werner, Oliver Wilhelm, Harald C. Traue, Ayoub Al-Hamadi, and Steffen Walter. "Multi-Modal Signals for Analyzing Pain Responses to Thermal and Electrical Stimuli." *Journal of Visualized Experiments*, no. 146 (2019). https://doi.org/10.3791/59057.
87. Pouromran, Fatemeh, Srinivasan Radhakrishnan, and Sagar Kamarthi. "Exploration of Physiological Sensors, Features, and Machine Learning Models for Pain Intensity Estimation." *PLOS ONE* 16, no. 7 (2021). https://doi.org/10.1371/journal.pone.0254108.
88. Amirian, Mohammadreza, Markus Kächele, and Friedhelm Schwenker. "Using Radial Basis Function Neural Networks for Continuous and Discrete Pain Estimation from Bio-Physiological Signals." *Artificial Neural Networks in Pattern Recognition*, 2016, 269–84.https://doi.org/10.1007/978-3-319-46182-3_23.
89. Gruss, Sascha, Roi Treister, Philipp Werner, Harald C. Traue, Stephen Crawcour, Adriano Andrade, and Steffen Walter. "Pain Intensity Recognition Rates via Biopotential Feature Patterns with Support Vector Machines." *PLOS ONE* 10, no. 10 (2015). https://doi.org/10.1371/journal.pone.0140330.
90. S. Jafar Ali Ibrahim and Thangamani, M "Proliferators and Inhibitors Of Hepatocellular Carcinoma", *International Journal of Pure and Applied Mathematics (IJPAM) Special Issue of Mathematical Modelling of Engineering Problems* Vol 119 Issue.15.
91. July 2018
92. Compound feature generation and boosting model for cancer gene classification Ibrahim, S. Jafar Ali Ibrahim., Affir, A.M., Thangamani, M. *International Journal of Engineering Trends and Technology*, 2020, 68(10), pp. 48–51.