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Facial Expressions as Behavioral Indicators for Assessing Pain using Machine Learning Models

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ABSTRACT

Pain is a symptom of a condition or disease. Pain experienced in the body is verbally reported to a health care giver. Currently there is no objective way to measure physical pain or discomfort one may be feeling. And so consequently, there is no way for caregivers to adequately assess patients in pain who cannot verbalize it, such as non-verbal, adult patients and young children. Facial expressions may be used as a behavioral indicator for evidence of pain which can then be used to communicate a patient's distress and pain severity. These facial expressions can be recognized through jaw clenching, eyebrow raising, and eye squinting. Machine learning with vision based algorithms may differentiate these behavioral face-indicators and assess the pain levels of nonverbal patients. There have emerged many vision based methods for predicting pain from face images. This review summarizes the development of pain recognition from facial expressive images or videos, datasets available for research, an overview of vision based methods using conventional and deep learning, the current challenges and limitations, and scope for improvement in future.

Introduction

Evolution has equipped us with a complex system for dealing with injury or physical distress associated with health conditions, many of which rely on certain behaviors as a means of communication. Scientists and health experts described 'pain behavior' for chronic pain in humans which use mostly various communicative methods (Fordyce, 1976). Facial expressions are a crucial aspect of human communication, conveying a wide range of emotions, and additionally, pain on the physical body. Charles Darwin attempted placing the research of pain behavior in his book "The Expression of the Emotions in Man and Animals" in 1872 (Darwin et al. 1998). He characterized the pain expression thus: "In pain the mouth may be closed compressed, or more commonly, the lips are restricted, with the teeth clenched or ground together the eyes stare widely as if in horrified astonishment". He focused on expressive behaviors as a means of understanding the origin and functions of motivational and affective states. Pain is a signal of injury or distress, and prompt detection can lead to timely treatment and improved patient outcomes (Fordyce, 1976). Humans have always been responsive to painful facial expressions. Therefore, pain detection from facial expressions has been a topic of interest in both medical and non-medical fields.

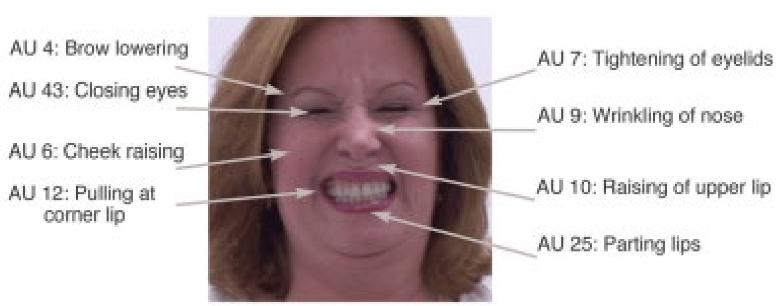

Fig. 1 Pain expressive face with action units (Lucey et al. 2009, https://ieeexplore.ieee.org/document/5349321)
There are several ways in which pain is expressed through facial expressions. These include furrowing of the brow, tightening of the jaw muscles, wrinkling of the forehead, and tightening of the eyelids (Fig. 1) (Lucey et al. 2009). The expressions may be subtle or pronounced depending on the level of pain. Therefore, it is important to consider these factors when developing pain detection systems.

One of the most common methods of pain detection from facial expressions is through manual observation by trained healthcare professionals. This method involves the clinician assessing the patient's facial expressions and assigning a pain score based on standardized scales. One example of such a system is the Pain Assessment in Advanced Dementia (PAINAD) scale, which uses facial expression, vocalization, body language, and consolability to assess pain in individuals with advanced dementia (Warden et al. 2003). The system has high sensitivity and specificity in detecting pain, even in individuals with communication difficulties. However, there is inter-rater variability, meaning different observers may assign different scores to the same facial expression. Additionally, it can be time-consuming and impractical in settings with limited healthcare resources.

To address the limitations, researchers developed computerized systems for pain detection from facial expressions. These systems use vision based algorithms to analyze facial expressions and detect pain based on patterns and features associated with pain expression. These systems can be trained on large datasets of facial expressions from individuals experiencing different levels of pain. During the last few decades, researchers studied pain related facial expressions, created datasets of images, and applied machine learning algorithms for detecting the pain levels with accuracy.

The objective of this review is to provide an overview on pain and development of automatic detection. For the methodology, a total of 48 relevant original and review articles were collected from Pubmed and IEEE Xplore. Key data and properties of the datasets were summarized. Additionally, I utilized personal experience from my research project and feedback from presentations at undergraduate research conferences to write this review. This review presents the basics of pain related facial expression, the datasets of images available, vision based methods used since 2011 from non-verbal face images such as conventional and deep learning, limitations and future scope.

The Painful Face

Pain is a very unpleasant sensation caused by illness or injury or it can be a mental distress or suffering (Breivik et al. 2008). It is a very individual feeling that is difficult to understand without any communication from the person who experiences pain. According to the National Centers for Health Statistics (www.cdc.gov/nchs), about 76.2 million people in the world suffer from pain physically. In clinical settings, reliably assessing and managing bodily pain is a difficult task. Patient's self-report is the most widely used technique to measure pain and is considered as the gold standard measurement of pain. Pain assessment using self-report measures is a significant challenge and is not always reliable and valid in critically ill adults, especially those who are unable to communicate their pain level. Also, self-reporting is not possible for unconscious or new born patients.

Quantifying The Facial Expression for Pain

The Facial Action Coding System (FACS) is a tool for the study of psychological and social parameter of pain as shown in Fig. 1 (Lucey et al. 2009) (Breivik et al. 2008). The changes in expression are described in terms of 44 action units (AUs), each of which is anatomically related to the contraction of a specific set of facial muscles movement, and were first developed by two scientists in the 1970s (Ekman and Friesen, 1978). In the 1990s, it was found that there are four actions: brow lowering (AU4), orbital tightening (AU6 and AU7), levator contraction (AU9 and AU10) and eye closure (AU43) that carry most information about pain (Prkachin, 1992). Scientists defined pain as the sum of intensities of brow lowering, orbital tightening (AU6 or AU7 (whichever is higher in intensity)), levator contraction (AU9 or AU10 (whichever is higher in intensity)) and eye closure. With the exception of AU43, each action was coded on a 5 level intensity dimension (A-E) by one of three coders who were certified FACS coders and AU43 was coded on a 2 level intensity scale i.e. either present or not. The Prkachin and Solomon Pain Intensity (PSPI) metric is defined as :

Pain= AU4 + (AU6 or AU7) + (AU9 or AU10) + AU43

A classic example provides a PSPI score in reference to Fig 1 (Lucey et al. 2011), wherein a particular frame which has been coded as 4A + 6D + 7D+ 12D + 43 by an expert FACS coder, then the PSPI value of that frame would be 1 + 4 + 1 = 6. Here AU4 refers to an intensity of 1, while AU6 and AU7 both have intensity of 4, so just the maximum 4 is considered, and AU43 has an intensity of 1 which is a value for the closed eyes in Fig 1. Currently the PSPI FACS pain scale is the only metric which can define pain on a frame by frame basis and is used for developing automatic detection.

Challenges with Face Images

Since facial action units and their intensity dimensions are the basis for automatic pain detection systems, the images and videos of face expression for machine learning require clarity and distinctiveness of facial features. Challenges in the real-world scenarios are found to be mostly digital or environmental (TABLE I). The challenges in digital imaging are poor illumination and low light condition in the capturing location and can lead to face expression not being clearly visible. This can decrease the prediction performance of automatic pain recognition. Also, pose variation by a change in the observer's observing angle or rotation in the head position, may make it difficult to recognize the input image and action units of a painful facial expression. The presence of objects that partially hide the face can also change how the face appears and create challenges for the vision based algorithms to detect the painful expressive faces. This problem occurs in real-world settings where people are on the phone, wearing hats, scarves, or glasses, or have hands covering their face. Another challenge is low resolution and blurred face images, such as motion blur from movement during image capture and out-of-focus blur (Lucey et al. 2011). Therefore, for scientific studies on face images datasets, such digital challenges hinder the accuracy of automatic recognition.

Another challenge in ensuring the quality of the face expression dataset is environmental. Distractions or clutter of an image or video causes scene complexity and adds to the difficulty of accurately recognizing and analyzing key facial landmarks, such as the position of the eyes, eyebrows, mouth, and other facial features that may be partially hidden. Moreover, a well distributed and diverse dataset of face types representing the variability of expressive faces in the target population is needed for good performance of a learning system. Finally, inherent variations among individuals, for example, the shape and structure of the face differ from person to person, including variations in the size and position of facial features such as eyes, nose, and mouth (Lucey et al. 2009). These variations can make it difficult to establish a consistent reference for feature detection and alignment across different faces, making it difficult for algorithms to accurately detect pain from the expressions.

Table 1: Challenges in Pain related Face Imaging

Challenges	Sub-Challenges
Digital Imaging	– Poor Illumination/ Low Light – Pose – Occlusion – Blur, Image Resolution
Environment	– Scene Complexity – Distribution of the Dataset – Variation in the Structure of Faces

The above challenges impact the quality, usability, and reliability of the data they provide. Addressing these issues requires careful data cleaning, validation, and verification processes.

Datasets Created for Research

For the pain detection research community, years of collaborations between clinical scientists, physicians, imaging experts and the algorithm developers has produced several reliable and usable datasets of pain expressive images. A brief summary of the benchmark datasets and their key characteristics for pain detection are presented in TABLE II.

Shoulder and Back Pain Datasets

The UNBC-McMaster Shoulder Pain Expression Archive Dataset, which is used heavily consists of face images from 129 adults, of which 63 and 66 are male and female, respectively (Lucey et al. 2011). The sequence level is self-reported via the Visual Analogue Scale, the sensory scale, the affective-motivational scale, and a PSPI score. The frame levels are comprised of 12 AUs, 66 facial landmarks, their intensities from A to E, and the PSPI score. The more recent EmoPain dataset contains healthy and chronic lower back pain data of 22 subjects aged 19 to 67, which consist of 7 men and 15 women (Aung et al. 2015). The dataset contains 44 videos, producing a huge number of pain frames of facial expressions.

Heat Pain Dataset

As new datasets are being created, more modalities are being incorporated. The BioVid Heat Pain Dataset has four levels of experimentally produced heat pain from 90 subjects (Walter et al. 2013). In order to account for different thermal pain sensitivities, the stimulation temperatures were modified based on the subject-specific pain thresholds and tolerances. In a random order, each of the four pain intensities was triggered 20 times. The facial EMG sensors and the unoccluded face were both used in the pain stimulation experiment twice. The dataset has four parts which are with or without facial EMG, short or long videos, those with partially occluded face, and the last one being posed and basic emotions, producing a total of 17,300 face images.

Table 2: Datasets for Pain Detection from Facial Expression

Available datasets	Features	Status	Devices Used	Pain Stimulus	Sample Size	Annotation or Labels Used
UNBC Dataset, 2011	Facial expression RGB	Shoulder pain	Two Sony digital cameras	Range of motion tests on shoulders	Frames Total: 48,398 Pain: 8369	12 AUs and their intensities from A to E, 66 facial landmarks, PSPI score
						Self-report via VAS, Sensory scale, Aff tive-motivational scale; Observer report via Observer Rated Pain tensity
EmoPain Dataset, 2015	Audio, Facial expressions, Body movements, sEMG	Chronic lower back pain	8 cameras -Animzaoo IGS-190 -BTS FREEEMG 300	Physical exercises	Frames Total: 585,487 Pain: 50,071	Pain, No pain
						Self-report of pain and anxiety on 1–10 sc
		Healthy			-	No pain
BioVid Heat Pain Dataset, 2013	Facial expression RGB, Biopotential signals (SCL, ECG, sEMG, EEG)	Healthy	Kinect camera - Nexus-32 amplifier	Heat	Total: 8700 videos Pain videos: 6960	baseline (no pain), 4 pain stimulus intens levels
					Total: 8600 videos Pain videos: 6880	baseline (no pain), 4 pain stimulus intens levels
					87 videos	pain stimulus
				Case Vignette	Total: 630 videos Posed pain videos: 90	7 posed expressions: neutral, pain, ang disgust, fear, happy, sad
DISFA Dataset, 2013	Facial expressions of emotion	Healthy	Stereo cameras	Heat	Video frames 4845	AU intensity was coded for each video fra on a 0 (not present) to 5 (maximum intens ordinal scale
X-ITE Pain Dataset, 2019	Facial expression RGB, Biopotential signals from cheek muscles	Healthy	Cameras - BioPac	Heat and electricity	-	Pain stimulus duration are 5s
UNBC- UNBC McMaster shoulder pain dataset; BioVid- BioVid Heat Pain Dataset; AUC- Area Under the Curve; PCC- Percentage of Correct Classification; ACC- Accuracy						

DISFA Dataset

The Denver Intensity of Spontaneous Facial Action (DISFA) dataset (Mavadati et al. 2013) contains about 130,000 annotated frames from 27 adult participants. Using the continuous measurement system (CMS), the intensity of 12 action units were manually labelled for each video frame on a six-point ordinal scale. The action units selected were those of the most prevalent in social interaction and emotion expression.

HIGH SCHOOL EDITION
Journal of Student Research

Electrical Stimulus Pain Dataset

The X-ITE Pain Dataset involves heat and electrical stimulus to induce pain in 134 healthy individuals with equal distribution of male and female, of ages 18 to 50 (Werner et al. 2019). These subjects did not have chronic pain, no neurological diseases, headache syndrome, cardiovascular illness, or history of psychological disorders as criteria for Healthy. A thermal stimulator was used to induce heat pain on the forearm. For gathering information on the multi-modal pain responses, numerous sensors were used. These were audio signals for measuring paralinguistic responses, RGB video of the face for facial expression and head pose, electrocardiogram, surface electromyography (EMG) for measuring muscle activity such as zygomaticus major muscle on the cheeks, and electrodermal activity (EDA) to detect sweating.

Challenges and Scope for Improvement of Datasets

These datasets have been immensely useful for researchers to examine machine learning methods to accurately assess pain. A piechart shown in Fig. 2 highlights the usage of these datasets in research studies. Approximately 70% of research papers since 2011 used the UNBC-McMaster dataset. The DISFA and X-ITE Datasets being more recent, 2% of all research papers so far have used it. The popularity and convenience of the UNBC dataset is evident as continues to be used. However, the success of using these datasets depends on the methods used for predictions of pain and no pain detection or pain intensities, and the accuracies of such predictions when tested.

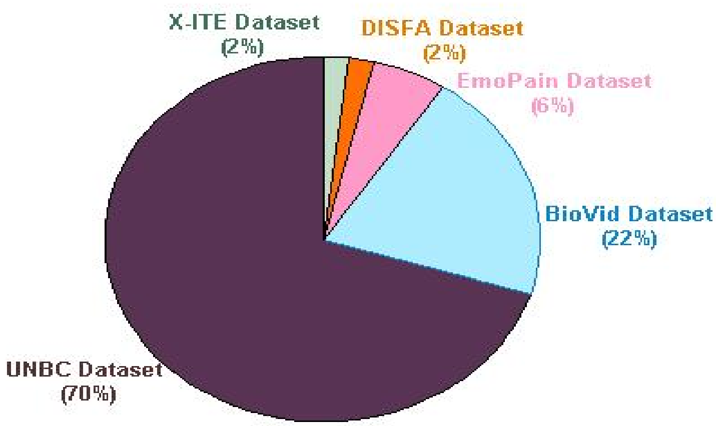

Fig. 2 Usage of current datasets in publications from 2011 to 2023

There is scope for improvement of datasets for the real-world challenges as the existing datasets do not address certain issues. For instance, in an uncontrolled setting, movements of head pose, body movements, and occlusions may occur. The differences in lighting conditions are also another set of variances that might happen in real-life scenarios. Secondly, using single modality image has its own drawbacks in providing all required information. Information from multiple imaging modalities may be more useful for clinical diagnosis and treatment monitoring. Most existing datasets do not consider multimodality based findings and provide a scope for the research community to design multi-modality_imaging datasets of painful facial expression towards a complex model design.

Conventional methods for pain classification

With advancements in computer vision and machine learning algorithms, automated systems have been developed to analyze facial expression, and detect and classify pain levels. A work flow diagram has been summarized (Fig. 3).

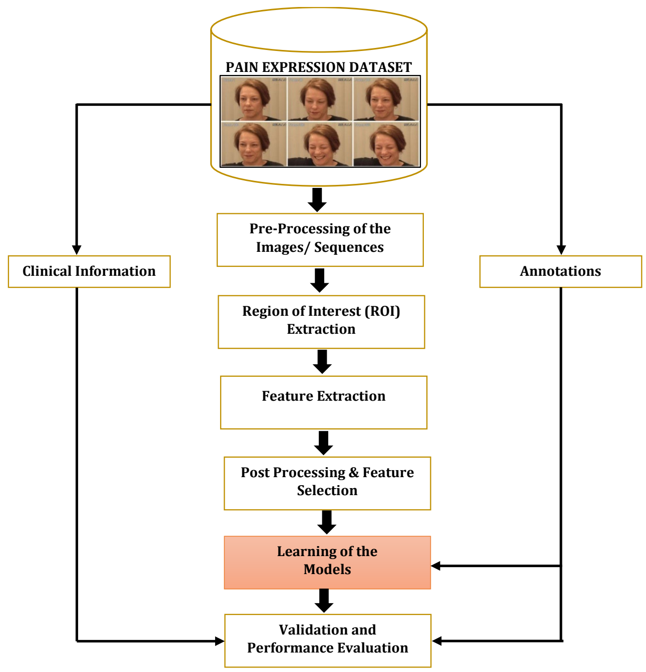

Fig 3: A General Workflow for Automated pain detection

The common part of the methods are extracting the regions of interest (ROI) and subsequently extracting specific features from the ROI, and then the facial images in the datasets are annotated with pain-specific expressions and action units. The learning models using computation techniques can be varied and improved to give a good prediction of accuracy.

Traditional machine learning models recognize patterns in facial muscle activity, wrinkle patterns, and overall facial dynamics. **TABLE III** is a literature survey of the datasets and classification method used and the performance metrics for the classifier which are as either accuracy (ACC), area under the curve (AUC) or percentage of correct classification (PCC).

Conventional methods for pain detection have utilized the UNBC and BioVid datasets. For many studies by using these datasets, traditional machine learning classifiers used include support vector nachine (SVM), multiple instance learning (MIL), multiple clustered learning (MCIL) and multi-task learning for pain detection in facial videos and images (Zhanli et al. 2019). One study employed a framework based on multi-view distance metric learning for pain detection and pain intensity asessment, for which they extracted three different handcrafted features i.e., Gabor features, Histogram of Orientation Gradient (HOG), and Local Binary Pattern from the facial expressive image sequences (Rathee, 2016). After that, they applied Multiview Distance Metric Learning (MDML) method on these extracted hand crafted features for complimentary features extraction, followed by classification by the traditional SVM, achieving 82.5% accuracy. More recently in 2023, Artificial Neural network (ANN) was used to perform binary classification into pain and no pain, with the objective to find the best suitable model, and which achieved the highest accuracy of 86% (Hadelina et al. 2023).

Hybrid frameworks were also examined for binary classification for pain and no-pain and also for detection of intensity of pain. A standard feature and speeded-up robust feature extraction was followed by dimensionality reduction using principal component analysis (PCA), linear discriminant analysis (LDA) and independent component analysis (ICA), and SVM for classification of pain its intensity (Singh, 2017).

Table 3: Conventional Methods for Pain Detection from Facial Expression

Author/ Year	Dataset used	Methods Used	Purpose	Performance Evaluation
Ashraf et al., 2019	UNBC/ Shoulder pain	Support Vector Machine (SVM)	Pain recognition from facial expression	AUC- 0.8113
Xu et al., 2021		Extended Multi-Task Learning	Pain detection in facial videos using individual models and uncertainty estimation	PCC- 50%
Meawad et al., 2017		Ambient Intelligence	Detecting pain from video frames	Precision- 94%
Anwar et al., 2021	UNBC and BioVid/ Shoulder pain, heat stimulated pain	Active Appearance Model (AAM), SVM	Pain detection of facial expressions	ACC- 0.893
Chen et al., 2019	UNBC/ Shoulder pain	Multiple Instance Learning (MIL) and Multiple Clustered Instance Learning (MCIL)	Pain detection at video-frame level and at video-sequence level	ACC- 87%; AUC- 0.94
Rathee et al., 2016		Gabor features, Histogram of Orientation Gradient , Local Binary Pattern, Multiview Distance Metric Learning, SVM	Pain detection and pain intensity detection	ACC- 82.5%
Hadelina et al., 2023		ANN (Artificial Neural Network)	No-pain and pain classification when a person is wearing a mask	F1-Score:- 79%
Singh et al., 2017	UNBC, BioVid, own dataset/ Shoulder pain, heat stimulated pain	SIFT, SURF, PCA, LDA, ICA, SVM	No-pain/ pain classification and pain intensity estimation	ACC- 87%
Chen et al., 2015	UNBC/ Shoulder pain	P-HOG, HOG-TOP, Multiple Kernel Learning (MKL), SVM	Pain event detection in video	ACC- 87.25%

Lopez-Martinez et al., 2017	BioVid/Heat stimulated pain	Multi task Neural Networks	Pain intensity measurement	ACC- 66.68%
Werner et al., 2016	UNBC and BioVid/ Shoulder pain, heat stimulated pain	Time series features, SVM	Pain detection and intensity estimation	ACC- 51.6%
Fatemeh et al., 2021	BioVid/Heat stimulated pain	Linear Regression, Support Vector Regression (SVR), Neural Networks, and Extreme Gradient Boosting	Automatic objective pain intensity estimation	Mean Absolute Error (MAE)- 0.93
Elgendy et al., 2021	Shoulder pain	Gabor filter, Relieff-SADE, Adaboost, SVM	Pain level classification	ACC- 86%
UNBC- UNBC McMaster shoulder pain dataset; BioVid- BioVid Heat Pain Dataset; AUC- Area Under the Curve; PCC- Percentage of Correct Classification; ACC- Accuracy				

A system for pain event detection from the video sequences used HOG from Three Orthogonal Planes (HOG-TOP) to extract spatial and dynamic features, and Multiple Kernel Learning (MKL) to fuse these features and perform pain detection using the SVM classifier (Chen, 2005). Some frameworks using other learning approaches had lower performances. (Lopez-Martinez, 2017) (Werner et al. 2016).

Deep Learning methods for pain classification

Deep learning based methods leverage the power of artificial neural networks to automatically learn features from facial images and classify them into pain or non-pain categories. Deep learning has high image classification ability. Among various deep learning based models, convolutional neural networks (CNNs) have been widely used for image recognition tasks. The network architecture consists of multiple convolutional layers, followed by pooling and fully connected layers. CNNs can learn hierarchical features from images, enabling them to capture spatial patterns in facial expressions that may be associated with pain.

Table 4: Deep Learning Based Methods For Pain Detection Or Intensity Classification

Author/ Year	Dataset	Method Used	Performance Evaluation
Karamitsos et al. 2021	UNBC/ Shoulder pain	Modified VGG-16	ACC- 92.5%
Bargshady et al. 2019		Vgg16 and Recurrent Neural Network (RNN)	ACC- 75.2%
Bellantonio et al. 2017		RNN and CNN	ACC- 63.47%
Alghamdi et al. 2022		Vgg16 and resnet50	ACC- 99.10%
Huang et al. 2020		Pain-Attentive Network (PAN)	PCC- 0.89
Huang et al. 2022		3D convolutional network	ACC- 0.82
Semwal et al. 2020		DCNN architecture	AUC- 0.97

Zhou et al. 2016		Active Appearance Model (AAM), RNN	PCC- 0.78
Tavakolian et al., 2020	UNBC/ Shoulder pain and BioVid /Heat stimulated pain	Statistical Spatiotemporal Distillation (SSD)	ACC- 0.76
Abedi et al. 2020	UNBC/ Shoulder pain	CNN+LSTM	ACC- 73.31%
Peng et al. 2020		Multi-scale deep network	ACC- 79.94%
Kharghanian et al. 2016		Convolutional Deep Belief Network (CDBN)	AUC- 95%
Rodriguez et al. 2017		VGG and LSTM	ACC- 95.85%
Xin et al. 2020		End-to-end attention network	ACC- 51.1%
Huang et al. 2022		Hierarchical deep network (HDN)	PCC- 0.78
Ragolta et al. 2020	EmoPain/ Chronic lower back pain	LSTM+RNN	PCC- 0.158
Li et al. 2021		LSTM+DNN	ACC- 94.08%
Dehshibi et al. 2023		sparsely-connected recurrent neural networks (s-RNNs)	F1-score- 83.78%
Subramaniam et al. 2020	BioVid/ Heat stimulated pain	hybrid CNN+LSTM network	ACC- 91.43%
Othman et al. 2019	BioVid/ Heat and X-ITE/ electrical pain	MobilenetV2 model	ACC- 67.9%
Barua et al. 2022	UNBC/ Shoulder pain and DISFA/ stimulated pain	Deep network Darknet19 Transfer learning, shutter blinds-based deep feature extraction	ACC- 95%
UNBC- UNBC McMaster shoulder pain dataset; BioVid- BioVid Heat Pain Dataset; EmoPain- EmoPain Dataset; X-ITE- X-ITE Pain Dataset; AUC- Area Under the Curve; ACC- Accuracy; CCC- Concordance Correlation Coefficient			

Using the very popular UNBC Mc-Master shoulder pain benchmark dataset, many authors report prediction accuracies of pain intensities using deep learning by proposing various frameworks and models as summarized in TABLE IV. Models examined are a modified VGG16 model, a recurrent neural network (RNN) and VGG16, and hybrid frameworks for facial video using a combination of CNN and RNN (Karamitsos et al. 2021)(Bargshady et al. 2019) (Bellantonio et al. 2017). A high accuracy of 99% for pain level predictions were obtained when two pre-trained CNNs used either VGG16, InceptionV3 or ResNet50, and a shallow CNN (Alghamdi et al. 2022). A deep spatio-temporal attention model called Pain Attentive Network (PAN) for extraction of dynamic features from facial expressive face images, and a network of spatial and temporal sub networks achieved a PCC of 0.89, which is considered as an acceptable prediction (Huang et al. 2020). Others used end-to-end hybrid network that combined 3D, 2D, and 1D convolution to extract multidimensional features from image sequences (Huang et al. 2022) or active appearance model (AAM) from the holistic image sequences with recurrent convolutional neural networks (RCNN) (Zhou et al. 2016). For videos, strategies such as a Statistical Spatiotemporal Distillation (SSD) method to encode statistical information (Tavakolian et al. 2020) were used, and Long-Short Term Memory (LSTM) model and CNN to identify and categorize pain expression were also employed (Abedi et al. 2020). A hierarchical unsupervised feature learning approach, where features were extracted using convolutional deep belief network (CDBN) gave a very high accuracy. Similarly, for video frames high accuracies were obtained when using CNN to learn facial features from VGG Faces and then appending LSTM to exploit the temporal relation between the video frames (Rodriguez et al. 2017).

More recently, when the Emopain chronic lower back pain dataset with face images was generated, studies reported their results of pain intensity prediction with various frameworks. High accuracy was obtained by a Pain Level Assessment with Anomaly-detection based Network or PLAAN in short, in a proposed ‘lightweight’ LSTM-DNN network (Li et al. 2021). This year, a sparsely-connected recurrent neural networks (s-RNNs) ensemble with gated recurrent unit (GRU) that incorporates multiple auto encoders using a shared training framework produced high accuracy (Dehshibi et al. 2023). Using the BioVid Heat Pain Dataset, another framework proposed an acute nociceptive pain recognition system using physiological signals and a hybrid deep learning network combining shallow CNN and LSTM network for pain intensity classification and achieved an accuracy of 91.43% (Subramaniam et al. 2020). An interesting study made use by combining the databases BioVid Heat and the X-ITE, and then validated two recognition methods, one being the Random Forest classifier with facial activity descriptors (FAD) and the second one being reduced MobileNetV2. These two methods showed consistent performance and combining data from both databases improved the results (Othman et al. 2019). Lastly, dynamic-sized horizontal patches called patch shutter blinds were introduced a new concept for feature extraction, and a lightweight deep network such as DarkNet19 pre-trained on ImageNet1K generated deep features from the input facial image, and the most discriminative features were then fed to a kNN classifier for pain classification, yielding accuracy of 95% (Barua et al. 2022).

Limitations and Scope for Improvement

A limitation of many neural networks is that it requires large amount of annotated data for training, which require tasks that are often time consuming. To advance the field of pain detection, the goals are to improve the performance of the learning methods, meaning the accuracy of detection, its sensitivity and specificity, and additionally, annotating the data should be less laborious.

A trained deep learning model ideally performs properly on test data when its distribution is similar to the training data. The majority of the studies on pain detection using facial expressions have used pre-trained CNNs as a fine-tuning module. The systems using facial expression must be able to adjust to the unique facial morphology, facial structure and texture, and pain expression of each subject. Domain adaptation techniques of computer vision can be applied, where a neural network that was trained on a source dataset is used to for testing accuracy on a rather different appearing target dataset (Csurka 2017). Also, Attention-guided CNN models may have promise as well, primarily because these models can provide spatial attention to certain semantic features of facial regions (i.e., regions of importance) that carries maximum information of the facial deformation related to the pain expressions (Niu et al. 2021). Therefore, even with all the developments so far, learning models have scope for improvement with more research that will progress this field.

Conclusion

Understanding and interpreting pain expression can help healthcare professionals and caregivers provide appropriate support and treatment to those in pain, and to non-verbal individuals. Machine learning techniques have been utilized to study and analyze pain expression in various contexts. Further pain detection research will adjust to the spatial aspects of the face expression image, examine various pain inducing modalities, and improve accuracies of detection.

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References

Abedi, WMS., Ahmed T. S., and Nadher, I., "Modified CNN-LSTM for Pain Facial Expressions Recognition." (2020).

Ahmed A., Yang A., and Taati. B. "Pain expression recognition using occluded faces." 2019 14th IEEE international conference on Automatic Face & Gesture Recognition (FG 2019). IEEE, 2019. https://doi.org/10.1109/FG.2019.8756594

Alghamdi, T., and Alaghband, G. "Facial expressions based automatic pain assessment system." Applied Sciences 12.13 (2022): 6423. 10.3390/app12136423

Anwar, D. A. "Real Time Pain Detection Using Facial Action Units in Telehealth System." http://dx.doi.org/10.21271/zjpas

Aung, M. S., Kaltwang, S., Romera-Paredes, B., Martinez, B., Singh, A., Cella, M., ... & Bianchi-Berthouze, N. (2015). The automatic detection of chronic pain-related expression: requirements, challenges and the multimodal EmoPain dataset. IEEE transactions on affective computing, 7(4), 435-451. 10.1109/TAFFC.2015.2462830

Bargshady, G., Soar, J., Zhou, X., Deo, R., Whittaker, F., and Wang, H. "A joint deep neural network model for pain recognition from face." 2019 IEEE 4th International Conference on Computer and Communication Systems (ICCCS). IEEE, 2019. 10.1109/CCOMS.2019.8821779

Barua, P. D., Baygin, N., Dogan, S., Baygin, M., Arunkumar, N., Fujita, H., Tuncer, T., Tan, R., Palmer, E., Azizan, M. M. B., Kadri, N. B., Acharya, U. R. "Automated detection of pain levels using deep feature extraction from shutter blinds-based dynamic-sized horizontal patches with facial images." Scientific Reports 12.1 (2022): 17297. 10.1038/s41598-022-21380-4

Bellantonio, M., Haque, M. A., Rodriguez, P., Nasorollahi, K., Telve, T., Escalera, S., Gonzalez, J., Moeslund, T. B., Rasti, P., and Anbarjafari, G. "Spatio-temporal pain recognition in cnn-based super-resolved facial images." Video Analytics. Face and Facial Expression Recognition and Audience Measurement: Third International Workshop, VAAM 2016, and Second International Workshop, FFER 2016, Cancun, Mexico, December 4, 2016, Revised Selected Papers 2. Springer International Publishing, 2017.

Breivik, H., Borchgrevink, P. C., Allen, S. M., Rosseland, L. A., Romundstad, L., Breivik Hals, E. K., ... & Stubhaug, A. (2008). Assessment of pain. BJA: British Journal of Anaesthesia, 101(1), 17-24. https://doi.org/10.1093/bja/aen103

Chen, J., Chi, Zheru., and Fu, H.. "A new apprach for pain event detection in video." 2015 International Conference on Affective Computing and Intelligent Interaction (ACII). IEEE, 2015. https://doi.org/10.1109/ACII.2015.7344579

Chen, Z., Ansari, R., and Wilkie, D. J. "Learning pain from action unit combinations: a weakly supervised approach via multiple instance learning." IEEE transactions on affective computing 13.1 (2019): 135-146. 10.1109/taffc.2019.2949314

Csurka, G. (2017). Domain adaptation for visual applications: A comprehensive survey. arXiv preprint arXiv:1702.05374.
https://doi.org/10.48550/arXiv.1702.05374

Darwin, C., and Prodger, P. (1998). The expression of the emotions in man and animals. Oxford University Press, USA. https://doi.org/10.1037/10001-000

Dehshibi, M. M., Olugbade, T., Diaz de Maria, F., Berthouze, N., and Jimenez, Ana. "Pain level and pain-related behaviour classification using GRU-based sparsely-connected RNNs." IEEE Journal of Selected Topics in Signal Processing (2023). https://doi.org/10.1109/jstsp.2023.3262358

Ekman, P., & Friesen, W. V. (1978). Facial action coding system. Environmental Psychology & Nonverbal Behavior. https://doi.org/10.1037/t27734-000

Elgendy, F., Alshewimy, M., and Sarhan, A. M. "Pain detection/classification framework including face recognition based on the analysis of facial expressions for E-health systems." Int. Arab J. Inf. Technol. 18.1 (2021): 125-132.

Fordyce W. E. (1976). Behavioral methods for chronic pain and illness. St. Louis, MO; Mosby.

Hadelina, R., Rusydi, M. I., Firza, M., Samuel, O. W. "ANN Models for Shoulder Pain Detection based on Human Facial Expression Covered by Mask." JITCE (Journal of Information Technology and Computer Engineering) 7.01 (2023): 49-55

Huang, D., Xia, Z., Li, L., and Ma, Y. "Pain estimation with integrating global-wise and region-wise convolutional networks." IET Image Processing 17.3 (2023): 637-648 https://doi.org/10.1049/ipr2.12639

Huang, D., Xia, Z., Mwesigye, J., and Feng, X. "Pain-attentive network: a deep spatio-temporal attention model for pain estimation." Multimedia Tools and Applications 79 (2020): 28329-28354. https://doi.org/10.1007/s11042-020-09397-1

Huang, Y., Qing, L., Xu, S., Wang, L., Peng, Y. "HybNet: a hybrid network structure for pain intensity estimation." The Visual Computer (2022): 1-12. https://doi.org/10.1007/s00371-021-02056-y

Karamitsos, I., Seladji, I., and Modak, S. "A modified CNN network for automatic pain identification using facial expressions." Journal of Software Engineering and Applications 14.8 (2021): 400-417. 10.4236/jsea.2021.148024

Kharghanian, R., Peiravi, A., and Moradi, F. "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). IEEE, 2016. 10.1109/EMBC.2016.7590729

Li, Y., Ghosh, S., and Joshi, J. "PLAAN: Pain Level Assessment with Anomaly-detection based Network." Journal on Multimodal User Interfaces (2021): 1-14. https://doi.org/10.1007/s12193-020-00362-8

Lopez-Martinez, D., and Picard, R. "Multi-task neural networks for personalized pain recognition from physiological signals." 2017 Seventh International Conference on Affective Computing and Intelligent Interaction Workshops and Demos (ACIIW). IEEE, 2017. 10.1109/ACIIW.2017.8272611

Lucey, P., Cohn, J. F., Prkachin, K. M., Solomon, P. E., & Matthews, I. (2011, March). Painful data: The UNBC-McMaster shoulder pain expression archive database. In 2011 IEEE International Conference on Automatic Face & Gesture Recognition (FG) (pp. 57-64). IEEE. https://doi.org/10.1016/j.imavis.2009.05.007

Lucey, P., Cohn, J., Lucey, S., Matthews, I., Sridharan, S., and Prkachin, K. M. (2009, September). Automatically detecting pain using facial actions. In 2009 3rd International Conference on Affective Computing and Intelligent Interaction and Workshops (pp. 1-8). IEEE.

Mallol-Ragolta, A., Liu, S., Cummins, N., Schuller, B. "A curriculum learning approach for pain intensity recognition from facial expressions." 2020 15th IEEE international conference on automatic face and gesture recognition (FG 2020). IEEE, 2020. 10.1109/FG47880.2020.00083

Mavadati, S. M., Mahoor, M. H., Bartlett, K., Trinh, P., & Cohn, J. F. (2013). Disfa: A spontaneous facial action intensity database. IEEE Transactions on Affective Computing, 4(2), 151-160. 10.1109/T-AFFC.2013.4

Meawad, F., Yang, S., and Loy, F. L. "Automatic detection of pain from spontaneous facial expressions." Proceedings of the 19th ACM International Conference on Multimodal Interaction. 2017. 10.1145/3136755.3136794

Niu, Z., Zhong, G., & Yu, H. (2021). A review on the attention mechanism of deep learning. Neurocomputing, 452, 48-62. https://doi.org/10.1016/j.neucom.2021.03.091

Othman, E., Werner, P., Saxen, F., Al-Hamadi, A., Walter, S. "Cross-database evaluation of pain recognition from facial video." 2019 11th International Symposium on Image and Signal Processing and Analysis (ISPA). IEEE, 2019 10.1109/ISPA.2019.8868562

Peng, X., Huang, D., and Zhang, H. "Pain intensity recognition via multi-scale deep network." IET Image Processing 14.8 (2020): 1645-1652 **https://doi.org/10.1049/iet-ipr.2019.1448**

Pouromran, F., Radhakrishnan, S., and Kamarthi, S. "Exploration of physiological sensors, features, and machine learning models for pain intensity estimation." Plos one 16.7 (2021): e0254108. https://doi.org/10.1371/journal.pone.0254108

Prkachin, K. M. (1992). The consistency of facial expressions of pain: a comparison across modalities. Pain, 51(3), 297-306. 10.1016/0304-3959(92)90213-U

Rathee, N., and Ganotra, D. "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
Rodriguez, P., Cucurull, G., Gonzalez, J., Gonfaus, J. M., Nasrollahi, K., Moeslund, T. B., Roca, F. X. "Deep pain: Exploiting long short-term memory networks for facial expression classification." IEEE transactions on cybernetics 52.5 (2017): 3314-3324. 10.1109/TCYB.2017.2662199
Semwal, A., and Londhe, N.D. "Automated Facial Expression based Pain Assessment Using Deep Convolutional Neural Network." 2020 3rd International Conference on Intelligent Sustainable Systems (ICISS). IEEE, 2020. 10.1109/ICISS49785.2020.9316099
Singh, S. K., Tiwari, S., Abidi, A. I., Singh, A. "Prediction of pain intensity using multimedia data." Multimedia Tools and Applications 76 (2017): 19317-19342. https://doi.org/10.1007/s11042-017-4718-6
Subramaniam, S. D., and Dass, B. "Automated nociceptive pain assessment using physiological signals and a hybrid deep learning network." IEEE Sensors Journal 21.3 (2020): 3335-3343. 10.1109/JSEN.2020.3023656
Tavakolian, M., Lopez, M. D., and Liu, L. "Self-supervised pain intensity estimation from facial videos via statistical spatiotemporal distillation." Pattern Recognition Letters 140 (2020): 26-33. https://doi.org/10.1016/j.patrec.2020.09.012
Walter, S., Gruss, S., Ehleiter, H., Tan, J., Traue, H. C., Werner, P., ... & da Silva, G. M. (2013, June). The biovid heat pain database data for the advancement and systematic validation of an automated pain recognition system. In 2013 IEEE international conference on cybernetics (CYBCO) (pp. 128-131). IEEE. 10.1109/CYBConf.2013.6617456
Warden, V., Hurley, A. C., & Volicer, L. (2003). Development and psychometric evaluation of the Pain Assessment in Advanced Dementia (PAINAD) scale. Journal of the American Medical Directors Association, 4(1), 9-15. https://doi.org/10.1097/01.JAM.0000043422.31640.F7
Werner, P., Al-Hamadi, A., Gruss, S., & Walter, S. (2019, September). Twofold-multimodal pain recognition with the X-ITE pain database. In 2019 8th International Conference on Affective Computing and Intelligent Interaction Workshops and Demos (ACIIW) (pp. 290-296). IEEE. 10.1109/ACIIW.2019.8925061
Werner, P., Al-Hamadi, A., Limbrecht-Ecklundt, K., Walter, S., Gruss, S., Traue, H. C. "Automatic pain assessment with facial activity descriptors." IEEE Transactions on Affective Computing 8.3 (2016): 286-299. https://doi.org/10.1109/TAFFC.2016.2537327
Xin, X., Lin, X., Yang, S., Zheng, Xin. "Pain intensity estimation based on a spatial transformation and attention CNN." Plos one 15.8 (2020): e0232412. 10.1371/journal.pone.0232412
Xu, X., and de Sa, V. R. "Personalized Pain Detection in Facial Video with Uncertainty Estimation." 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). IEEE, 2021. 10.1109/EMBC46164.2021.9631056
Zhou, J., Liu, K., Xu, L, Lai, S. 2016. "Recurrent convolutional neural network regression for continuous pain intensity estimation in video." Proceedings of the IEEE conference on computer vision and pattern recognition workshops. 10.1609/aaai.v29i1.9513