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DEEP LEARNING BASED MODEL FOR PAIN RECOGNITION FROM FACIAL EXPRESSION

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ABSTRACT

Recognition of pain is allowing a range of diagnosis and care possibilities in patients who cannot articulate themselves. Despite developments in this area there is still a lack of study, particularly under unfavorable conditions, on the identification of pain in live videos. Due to patient self report, pain is normally measured. However, self-reported pain is difficult to understand and may not be affected or even probable in certain cases (i.e. young children and those chronically ill). Conduct scientists have found accurate and valid face markers of pain in order to prevent certain issues. In this essay, we discuss an approach to acute pain without the need for human observators automatically. In particular, in adult patients our research was limited to the automatic diagnosis of pain. This paper introduces a deep learning system for the automated pain detection of RGB images taken by a single camera. It de-identifies the confidential information found in the original photos and preserves the privacy of computers that is highly significant. The experiments with challenging pain datasets in the real world show that our method effectively converts pain detection sensibilities from synthetic to actual data and achieves high data accuracy that demonstrates that pain detection in unknown real world surroundings can be generalized in an extremely accurate way.

Keywords: *Pain Recognition, Deep Convolutional Neural Network, Deep learning.*

1. INTRODUCTION

In recent years huge quantities of research has been done on automatic video sequence recognition (such as pain, rage, and sadness). Double is a subjective and personal experience and it is also difficult to perceive pain. Many possible applications for the recognition of pain are available. This subjectivity contributes to medical and treatment issues for patients. A clinical criteria for the diagnosis of underlying disorders, which in some cases are not known, is useful for assessing pain. Doctors consider pain when patients are in real pain, such as small children who could not disclose pain measures or several patients in postoperative or intermittent states of consciousness, and extreme respiratory problems, etc., are taken seriously. [1, 2]. The automated system can be trained in real-time, which could deliver major benefits in patient care and reduction of costs. Therefore, it is critical for patients to correctly identify pain arising in a clinical setting.

The pain measurement is usually performed through self-reporting, external evaluations, or physiological assessments. Of the three types, self-reporting is most desirable in which patients explain their own symptoms and experience. External observation facilitates and requires time, while physiological studies require that specialized equipment be used and possessed that cannot always be made available. The field of computer vision has progressed such that we can now begin to apply automatic systems to recognize facial expression to critical behavioral research issues. The paper is one of the first implementations of fully automatic measurement of facial expression for research issues. Measuring or tracking of pain typically happens by self-report, so it is easy and requires no specific expertise or personnel. Yet self-reporting methods cannot be used because it is difficult for patients to verbally communicate. Many researchers aimed at continuous objective pain assessment by tissue pathology analyzes, neurologic "signatures," imaging techniques, muscle strength tests, and so forth. [3].

A systematic problem that needs to be solved with a powerful approach focused on deep education is automated pain recognition. Recently, some pain recognition experiments have used machine learning. This research therefore only aims at exploring demands for the deep learning of pain recognition. Deep learning is an important machine learning branch that can be used for several different applications. The way to achieve regulated learning is strong. Facial expressions are signals which have gained researchers' attention in many applications, such as biometric facial recognition.

Deep learning is directly used to estimate facial pain. The auto-reported visual analog scale (VAS) pain assessment for individual differences is one of the distinctive approaches. This is a model type used to estimate binary pain (pain, no pain). They presented an overview of earlier work on the common pain-detection data collection. This archive is classified as a UNBC-McMaster database and consists of 200 video sequences from 25 patients with shoulder pain. Your studies with this dataset have shown that your method is above all previous works with a region below the curve. Their model can be applied to other facial emotional recognition applications as well. The suffering is also mirrored in changes in facial expression. Facial expression is also considered the most accurate knowledge source in the assessment of another person's pain severity.

The paper is organized accordingly. We identified pain extraction from the deep convolution models of the neural network, following a review of related work in this section. Section 4 offers experimental PainNet model information for pain expression recognition. In the final section the conclusions are given.

2. RELATED WORKS

Several reports have investigated the efficiency and value of automated monitoring of facial expression, particularly pain. As part of the adopted hybrid model, the analysis used ownvectors. The researcher introduced the idea of a neural network to help classify painfully. For a model used to sense and identify pain, Monwar and Rezaei introduced their own imagery. As a suitable method of detecting pain Monwar et al. (2007) explored the use of those images. From video input faces were identified by skin color data and pain detection pictures were used. Overall, it was concluded that while the device had satisfactory performance, it was important to concentrate on video sequences in real-time. A structural analysis of pain-recogence programs based in the last two years is supported by Rasha M. Al-Eidan et al. (2020). In addition, the key methods of profound learning used in the analysis documents are discussed. Finally, it addresses the obstacles and unanswered questions.

Initial findings from the application to spontaneous facial expressions of pain from an automatic facial recognition device are provided by Gwen C. Littlewort etal. (2017). 26 participants were taped into three experimental conditions in this study: baseline, pain and true pain. The subjects endured cold pressing discomfort when their arm was submerged in ice water. Our objective was to decide automatically which test condition in a 60 second clip was seen. A hybrid model that enables efficient pain recognition has been proposed by Pranti Dutta et al. (2018). A hybrid that included a combination of CLM and Active Appearance Models and Patch-Based Models in accordance with image algebra has been applied.) The combination of CLM and AAM was implemented. This led to a system that allowed pain from a live stream to be detected successfully, even with low lighting and a low-resolution screen.

Shaoping Zhu (2019) introduces the latest approach in which pain expressions from a video sequence are automatically recognized that divides pain into four levels: 'no pain,' 'light pain,' 'moderated pain and' 'extreme pain.' Firstly, knowledge of facial velocity used to discern pain is identified by means of optical flow. In order to enhance recognition precision, the final pLSA model is used to understand the pain of speech and the class mark information has been used to learn the pLSA model. Experiments were carried out on a self-constructed pain expression dataset. Yi Li et al. (2021) proposes an anomaly-based pain assessment network to resolve a current cap. The assessment of the network is carried out using the EmoPain Challenge Dataset for estimating pain severity and estimating defensive behavior from body movements. The EmoPain dataset contains sensor data for both tasks depending upon the body component. The proposed network, PLAAN, is a light weight LSTM-DNN network based on sensor data which considers the input and predicts pain intensity and the presence or absence of protective behavior in chronic patients who have a low back pain.

A real-time real-worround pain sensing device from human facial expressions is developed by Laduona Dai et al. (2019). Although several studies have dealt with this problem, many of them use the same training and test data set. No testing on the output of new data is possible for other datasets or real time implementation. As illustrated in this paper, this is problematic because train classifiers on data set unique characteristics. The author discusses numerous methods of pain detection in

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real time. Unlike other articles, the training data incorporates pain and emotional data. MD Kamrul Hasan et al. (2016) explored how mobile apps can play a critical role in assisting patients in this situation. In order to detect pain precisely, the author has used facial images captured via smartphones. Current algorithms and infrastructure are used to make cancer patients accessible and user-friendly in this pain-detection process. The first smartphone research is the pain relief approach. In order to identify faces, the proposed algorithm is used, as a weighted combination of Eigenfaces.

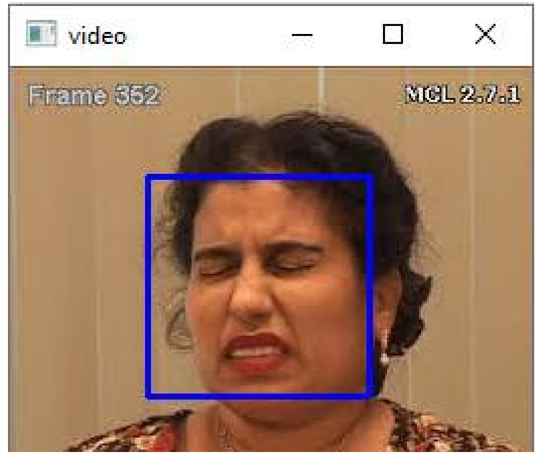
Ahmed Bilal Ashraf et al. (2009) are exploring an approach that allows acute pain to be identified automatically without human observers. Specifically in adult patients with rotator mango injuries our research has been restricted to automatically detecting pain. The machine used patients' video inputs when pushing their damaged shoulder. We also considered two kinds of ground truth. The ground truth on a sequence level consisted of scores in Likert form by trained observers. The truth of the ground level was determined based on presence/absence and the severity of previously paint-related facial behavior. Responsive appearance (AAM) models were used in digital face images to disconnect form from appearance.

3. PROPOSED METHODOLOGY

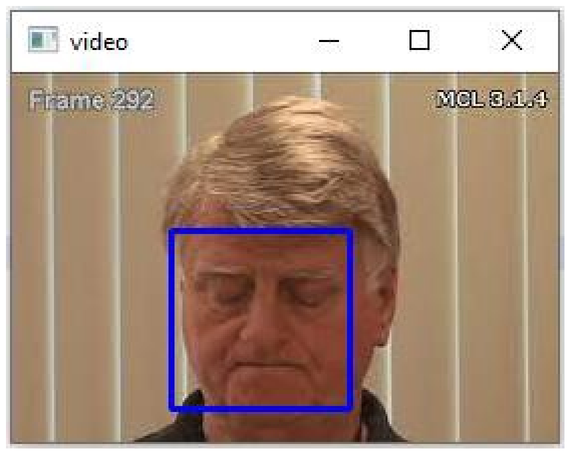
In this section we give a brief introduction to the pain recognition system proposed and the process definition.

3.1 Face Deection

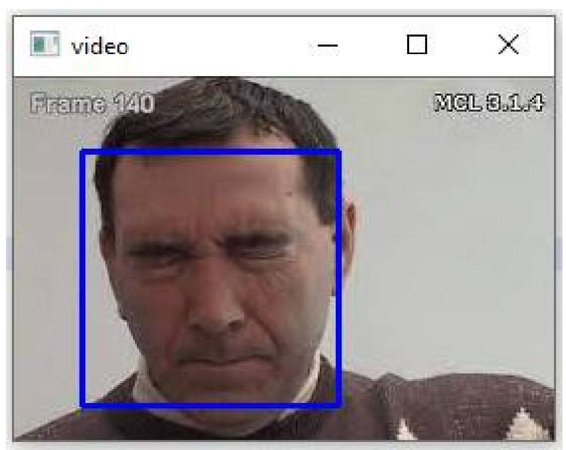
We deliver a deep learning architecture in this paper that utilizes RGB images for the detection of face pain. Our work varies in many ways in contrast with existing methods. Next, with various Hare Casscade classifiers, our system combines eye and mouth detection.



(a)



(b)



(c)

Figure 1: (a), (b) and (c) Face Detection of different style pain expression

3.2 Deep Convolutional Neural Networks

Figure 2 shows the overall architecture of our system, which has three principal sections, namely

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Convolution layer, sub-sampling layer and fully integrated layer. PainNet is a CNN model focused on visual representation and segmentation of the RGB image and learns high-level pain-recognition integration functionality. The various components of the conceptual system are explained in detail below.

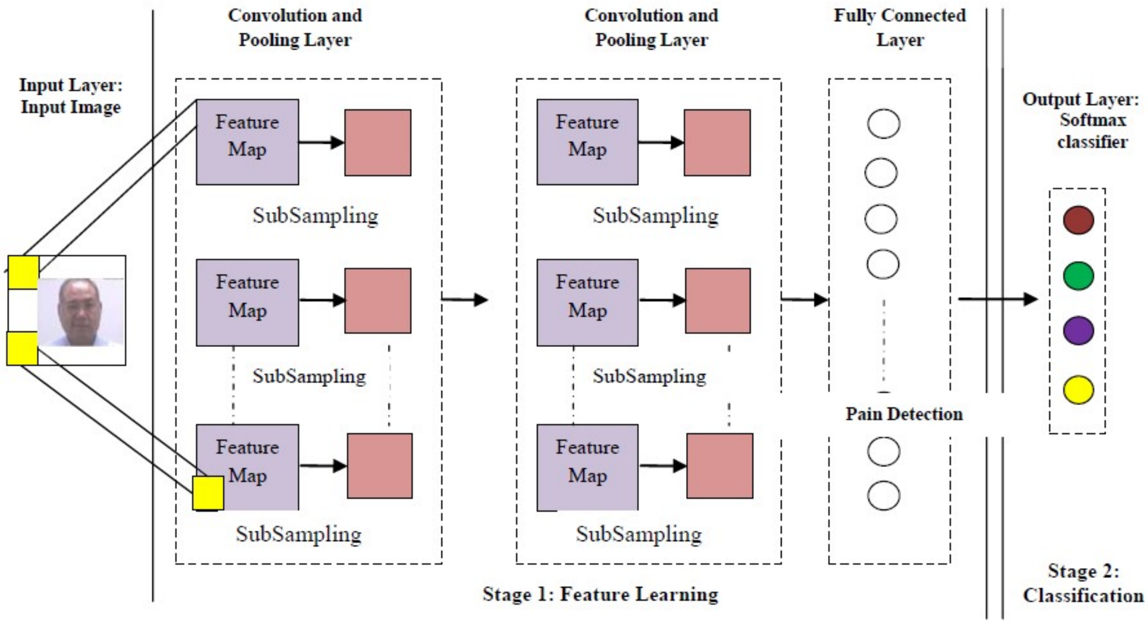

Figure 2: Overall Architecture for PainNet model

3.3 Training and Implementation

First, initialized the weights of the networks of the PainNet Model. For PainNet, initialized the weights of the convolutional layers with the weights of the embedding layers with zero-mean Gaussian distributions (standard deviations were set to 0.01 and biases were set to 0). For 20 epochs the educated convolutionary and the embedding layers are end-to-end. The starting learning rate was set to 0.01 and divided by 10 at 50% and 75% of the total number of epochs. The parameter decay was set to 0.0003 on the weights and biases. Our implementation is based on the framework of Torch library Paszke et al. (2017). Training was performed using ADAM optimizer. Figure 3 shows the convolution visualization of the one to six convolution processes.

Table 1: Summary of the PainNet Model

Layer type	Filter size & Stride	Details	Output Shape
Conv1	3x3 & s =1	Conv1 (16)	255,225, 16
Activation	ReLU		255,225, 16
MaxPooling		Pooling Size (2,2)	127,127, 16
Conv2	3x3 & s =1	Conv2 (16)	127,127, 16
Activation	ReLU		127,127, 16
MaxPooling		Pooling Size (2,2)	63,63,16
Conv3	3x3 & s =1	Conv3 (32)	63,63,32
Activation	ReLU		63,63,32
MaxPooling		Pooling Size (2,2)	31,31, 32
Conv4	3x3 & s =1	Conv4 (32)	31,31, 32
Activation	ReLU		31,31, 32

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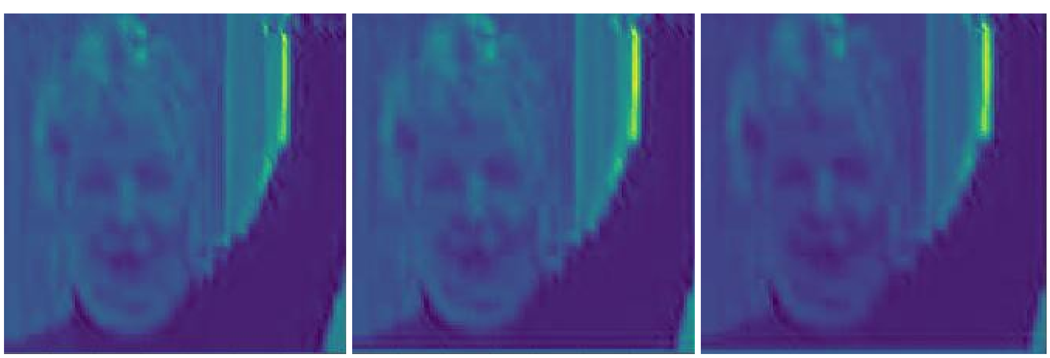
MaxPooling		Pooling Size (2,2)	15,15,32
Conv5	3x3 & s =1	Conv5 (64)	15,15,64
Activation	ReLU		15,15,64
MaxPooling		Pooling Size (2,2)	7,7,64
Conv6	3x3 & s =1	Conv6 (64)	7,7,64
Activation	ReLU		7,7,64
MaxPooling		Pooling Size (2,2)	3,3,64
Flatten	Flatten to a vector		96,756
Dense	Dense Input =256		256
Dense	Input Classes = 3		3
Activation	Softmax		3

(a) Input image

(b) Convolution_1 (c) Convolution_2 (d) Convolution_3



(d) Convolution_4 (e) Convolution_5 (f) Convolution_6

Figure 3: One to six convolution visualization for input image

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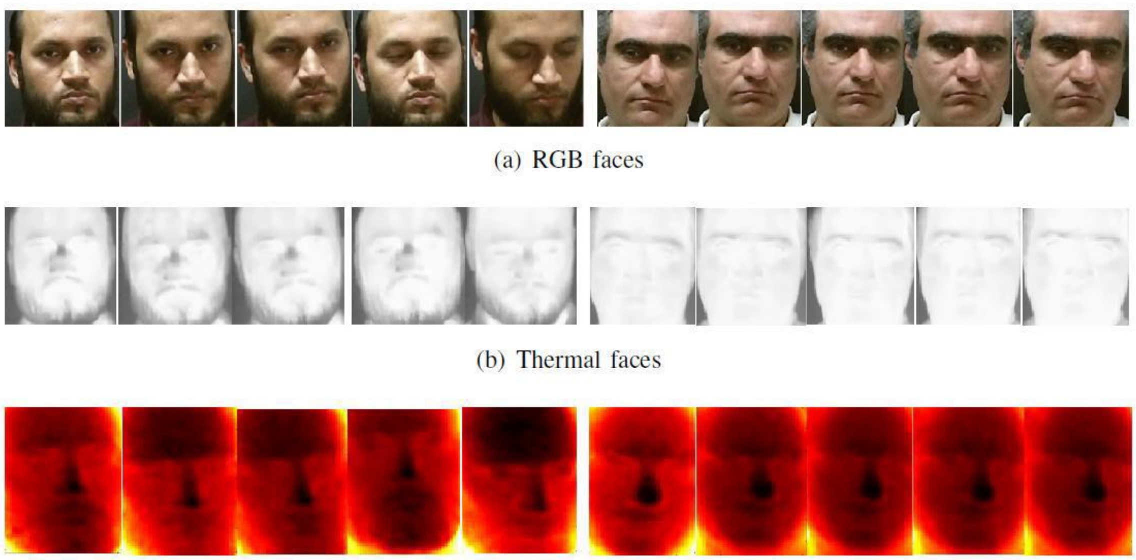
4. PROPOSED METHODOLOGY

4.1 Datasets

Table 2: Center Table Captions Above The Tables.

Attribute	**UNBC – McMaster database (2011)**	**BioVid Heat Pain database (2013)**	**MIntPain database (2018)**
No. of Subjects	129 (16 are available)	90 (87 are available)	20
Subject's type	Self-identified pain patient	Healthy voluteers	Healthy volunteers
Pain type	Natural sholder pain	Stimulated heat pain	Stimulated electrical pain
Pain levels	0-16 (PSPI) and 0-10 (VAS)	1-4 (Stimuli)	0-4(Stimuli)
Modalities	RGB	RGB	RGB, Depth, Thermal
Size of the database	200 variable length videos with 31,571 frames	17,300 5s videos with 25 fps	9366 variable length videos with 1,87,939 frames



(a) RGB faces

(b) Thermal faces

(c) Depth faces

Figure 4: Sample frames for MIntPain database

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Figure 5: Sample frames for UNBC – McMaster database

Figure 6: Sample frames for BioVid Heat Pain database

4.2 Evaluation Metrics

Figure 8 Illustrates a confusing matrix of true positive (TP), false positive (FP), true negative (TN) and false negative (FN) class values for a pain detection issue. If the classifier predicts correct class response in each instance and is considered "success," if not "error."The classifier's overall performance is obtained by error rate, which is a proportion of the errors made over the whole set of instances.

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Actual Value

Predicted	Positive	Negative
Positive	True Positive (TP)	False Positive (FP)
Negative	False Negative (FN)	True Negative (TN)

Precision (P) or detection rate is a proportion of properly marked instances and total instances. It can calculate the prediction model and is also known as a true positive figure. It is defined by:

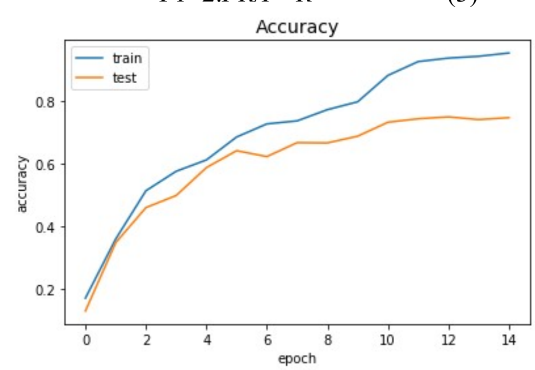
$$Precision(P)=TP/\ TP+FP \quad (1)$$

Recall (R) or Sensitivity is the proportion of properly named class instances and total instances. It can calculate the prediction model and is also known as a true positive figure. It is defined by:

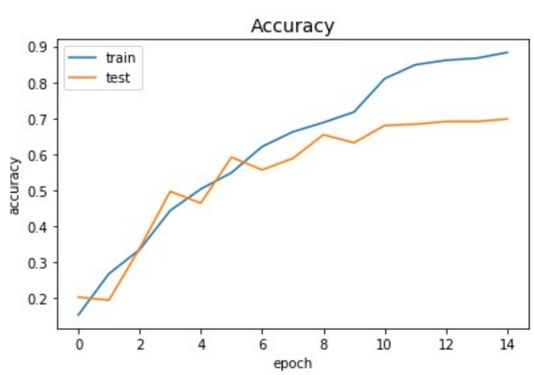
$$Recall(R) = TP/\ TP+FN \quad (2)$$

The F-measure is the harmonic mean of precision and recall and it attempts to give a single measure of performance.

$$F1=2.PR/P+R \quad (3)$$



(a) Accuracy for 'ReLU'



(b) Accuracy for ELU

Figure 8: Accuracy of proposed model for different activation function

In this experiment, 70% of Pain Video Dataset are used to train our pain detection models, and last 30%of the dataset is used to test the models. The efficiency of pain detection is expressed mainly in terms of precision, recall, and f-score. The f-score is the ability to properly classify a pain as a pain, while the accuracy is the ability to properly classify a pain as a dropping.

Table 3: Confusion Matrix for Pain detection in (%) for UNBC – McMaster database

	Neutral	Pain	Non Pain
Neutral	98	0	2
Pain	0	100	0
Non Pain	2	0	98

Table 4: Performance Metrics of Pain Detection using PainNet for UNBC – McMaster database

	Precision	**Recall**	**F1-score**
Neutral	0.80	0.91	0.87
Pain	0.81	0.93	0.88
Non Pain	1.00	1.00	1.00

From Table 4, we can see that the average sensitivity of our precision is 96.2% and the average f1-score is 98.1%.Experiment one's performance is the highest, because in Pain Dataset there is only one same human entity. Our dataset includes an elderly male, so we conjecture that pain detection will be harder in this experiment.

Table 5: Confusion Matrix for Pain detection in (%) for MIntPain database

	Neutral	Pain	Non Pain
Neutral	97	1	2
Pain	0	99	1
Non Pain	2	2	96

Table 4: Performance Metrics of Pain Detection using PainNet for UNBC – McMaster database

	Precision	**Recall**	**F1-score**
Neutral	0.79	0.89	0.88
Pain	0.78	0.91	0.86
Non Pain	0.98	0.99	0.99

From Table 6, we can see that the average sensitivity of our precision is 95.7% and the average f1-score is 97.3%.Experiment one's performance is the highest, because in Pain Dataset there is only one same human entity. Our dataset includes an elderly male, so we conjecture that pain detection will be harder in this experiment.

Table 7: Confusion Matrix for Pain detection in (%) for MIntPain database

	Neutral	Pain	Non Pain
Neutral	96	2	2
Pain	1	98	1
Non Pain	1	2	97

Table 8: Performance Metrics of Pain Detection using PainNet for UNBC – McMaster database

	Precision	**Recall**	**F1-score**
Neutral	0.78	0.88	0.86
Pain	0.79	0.90	0.85
Non Pain	0.97	0.98	0.98

From Table 8, we can see that the average sensitivity of our precision is 94.9% and the average f1-score is 96.4%.Experiment one's performance is the highest, because in Pain Dataset there is only one same human entity. Our dataset includes an female, so we conjecture that pain detection will be harder in this experiment.

Figure 9: Pain Detection from UNBC – McMaster database

4. CONCLUSION

The present study proposed that the pain-expression on subjects' faces should be calculated using videos and real-time streaming data as feedback by using a hybrid model and image algebra. This method succeeded because it was able to differentiate reliably between pain and painless expressions, although it was exposed to a range of unfavorable conditions, such as inadequate lighting, shifts in the head position, occlusions and pain integration into a sequence of other expressions. The recognition of pain can provide major benefits in the treatment of patients and decreases costs. This paper offers a new way to accept the expression of pain and simultaneously offer pain level. Experiments were conducted with a self-made pain expression data set and the suggested approach was tested. Experimental findings indicate that the approach proposed is better than previous methods.

A potential future research is to experiment with transfer learning techniques from MOCAP datasets to EmoPain data set for the sharing of subject movements by means of neural network weights. The features are taken from the body sensors which, because of cinematic constraints of the human body, have an inherent fixed nature. Therefore, to explore the graph convergence network for the job will be interesting.

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