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RESEARCH PAPER

Real Time Pain Detection Using Facial Action Units in Telehealth System

Dalya Abdullah Anwar
Department of Computer Science and information technology, College of Science, Salahaddin University-Erbil, KRG-Iraq.

A B S T R A C T:

During the Covid-19 pandemic, to reduce staff exposure to ill people, minimize the impact of patient surges on facilities, and preserve personal protective equipment, the recommendations are made by the World Health Organization to change the way that health care is delivered. Several telehealth systems are utilized including live audio-video interaction or real-time telephone typically with a patient using a computer, smartphone, or tablet. During these appointments, the doctors need to know the pain levels of the patient to be able to prescribe the correct medicine and diagnose the disease proficiently. In this paper, a real-time 4-pain levels recognition based on facial expression during telehealth is proposed. Generally, the pain is measured via verbal communication, normally the patient's self-report. However, if the patient has a disability and unable to communicate with others due to being impaired mentally or having breathing problems or the child self-reporting may not be a perfect way to measure the pain. The proposed system consists of two methods to detect pain from a patient's facial expressions. The AAM_Based method detects the face and facial landmarks from each video frame using Active Appearance Model AAM, these landmarks are used to compute the facial features. The AU_Based method uses Facial Action Units AU which objectively describes facial muscle activations that are considered as Region of Interest. Support Vector Machine classifier is utilized to detect the levels of pain. A labeled dataset such as Biovid is used to train test, and the AAM_based method, while and UNBC is used for the second method. The findings show that it is possible to depend on facial expression to detect pain level 1 and level 4 very accurately, while it is very tricky to detect pain level 2, and 3 because the AUs for them are similar for most of the patients.

KEY WORDS: Pain assessment, Face expression, AAM, SVM, COVID-19, Telehealth.
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1.INTRODUCTION :

Globally, the pandemic virus called COVID-19 has infected about 1.6 million patients and killed around 100,000 patients all around the world since April 10, 2020 (Mervosh et al, 2020). The daily lives of everyone have been affected by this virus (Isaac et al, 2020). People have been to stay at home. Several businesses had to transition into telehealth or virtual by using online video conference software such as Zoom, Google meet, and WebEx (Hardy, 2020). Recently, many pain assessment applications have been developed, however, most of them are dependent on subjective self-reported pain levels and suffering low accuracy rate (Rosser and Eccleston, 2012).

* **Corresponding Author:**
Dalya Abdullah Anwar
E-mail: dalya.anwar@su.edu.krd
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Pain assessment using facial expression is an important subject and attracts the researcher's attention in the field of computer vision (Craig, 1992, Craig et al, 2011) and deep learning approaches (Werner et al, 2012, Kächele et al, 2015). The social context and personal factors are influence pain expression directly (Prkachin and Craig, 1995). The main advantage of using facial expression to detect the pain levels is to reduce the distress caused by recording the brain activities or other physiological signals such as electrocardiogram ECG and electromyogram EMG that required sensors to be contacted directly to patient's body/skin (Kunz and Lautenbacher, 2019). An international competition aimed to create a platform for the comparison of multimedia processing methods of chronic pain assessment form human behavior and multi-model machine learning is conducted by the EmoPain 2020 challenge team (Egede et al., 2020).

Many researchers avoid the expressiveness problem while investigating an automatic pain recognition system and prefer visible pain reaction to label the video frames or images (Lucey et al, 2012, Kaltwang et al, 2012, Sikka et al, 2014, Rudovic et al, 2015). The main problem while evaluating several proposed methods is that the subjects show no facial reaction to pain (Kunz and Lautenbacher, 2014). A wrist-worm EDA device that transmits pain information and displays it into the user's smartphone via Bluetooth is proposed (Kong et al, 2020). Detecting pain levels for cancer patients via smartphone is proposed using their facial expression, the proposed method applied angular distance and SVM for the classification of the system (Hasan et al, 2016). Extensive research is detecting pain levels deploying the Facial Action Coding System (FACS) especially from human facial emotion (Ekman and Friesen, 1978). A facial emotions detection system using the Active Shape Model and SVM is utilized to identify the patient's psychological state in real-time (Anwar et al, 2016).

A stress detection of a smartphone user using an electrical dermal activity is proposed (Ayzenberg et al, 2012). A proposed method consists of three stages is proposed, the first stage is called the pre-processing stage, where the face is detected from each video frame, cropped, resized, and normalized using image processing methods. The next stage is called the feature extracting stage, in this stage, the facial features are extracted using the fine-tuned pre-trained CNN framework, then PCA is applied to reduce the extracted features dimensions. The third stage is called, the classification stage, in this stage an Enhanced Joint Hybrid classifier approach such as BilSTM is proposed to obtain the pain severity level (Ghazal Bargshady et al, 2020).

A study aims to provide a systematic review of deep learning applications only for pain detection is presented. The study aims to help the researchers in AI to know the deep ANN methods, used datasets, and tools needed to build a smart automatic pain detection system (Al-Eidan et al, 2020). Another study that focuses on analyzing the communication between measurements of pain and their prediction from a deep learning method is proposed. The authors explore several ways of using FACS Action Units AUs to combine them with their proposed extended multitask learning model (Xu & de Sa, 2020). Deep learning is utilized to train dataset and activity method to guide patient orientation, the method separated pain thresholds into 3 stages: no pain, start having pain, having pain (Pikulkaew, 2021). Deep convolution neural network DCNN is employed to detect pain, the proposed method is evaluated and tested using UNBC-McMaster shoulder pain dataset (Semwal et al, 2021).

In this paper, the contribution can be summarized in the following:

1. Building an automatic real-time pain detection system during a telehealth system.
2. Delivering the detected pain levels in a CSV format to the physicians to help them diagnose and treat the patients accordingly.
3. Utilizing two labeled datasets that content a to enhance pain detection reliability.
4. Calculating and adding three pain levels equations to the UNBC dataset, those pain levels are PA1, PA2, and PA3. Adding the three computed pain levels equations helped during the training process and improved the detection accuracy of the proposed method.
5. Comparing two methods for pain detection based on the patient's facial expression.

The work in this paper is arranged as follows: In section 2, the datasets are described. Section 3 includes the components of the developed method. Section 4 shows our findings. Section 5 includes the conclusion and future research.

2.DATASETS

A. Bovid Heat Pain Dataset

Heat with 4 intensities is used in the Biovid dataset to induce pain. Each subject in the dataset has a pain tolerance pain threshold used to adjust the temperature of the heat. In the Biovid database, there are 87 subjects and 5 pain levels, those levels are pain-baseline, L1, L2, L3, and L4. There are 20 samples for each class, each sample is 5 seconds in length, and the stimuli of the heat last for about 4s and have around 12s pause (The biovid heat pain database, 2021). In this paper, the Biovid dataset is used with AAM_based method.

B. UNBC Shoulder Pain Database

The facial expression of 25 subjects suffering from the pain of their shoulder is utilized to record 200 video series in UNBC Shoulder (upper back) Pain dataset (Prkachin et al, 2011). In total there are 48,398 frames coded using FACS (facial action coding system) (Friesen et al, 2002). For each frame in the UNBC dataset, there are pain scores depend on Prkachin and Solomon Pain Intensity (PSPI) scale. PSPI scale computed based on Facial Action Coding System FACS code that used tool for describing facial movements. The FACS code includes 9 different Action Units AUs in upper part of the face, 18 AUs in lower part of the face, and 5 AUs in neither lower nor upper part of face. Moreover, the FACS defines 11 AUs for head position, 9 for describing states of eyes, and 14 for other actions. Prkachin and Solomon are calculated pain level 4 using the FACS code. Below is the equation to calculate PSPI with the help of FACS for pain level 4. Other pain levels are calculated using PSPI with/out AU43, AU9, or AU6 (Prkachin and Solomon, 2008).

$$PSPI = AU34+(AU7 \text{ or } AU6) + (AU10 \text{ or } AU9) +AU4 \quad (1)$$

As shown in the above equation, the PSPI final score is the result of adding Action Unit AU7, AU6, or Au4 (the higher intensity AU will be added), Au9, or Au10 (the higher intensity AU will be added), and AU43. Figure 1 shows the AUs used in equation 1. Each AU is coded in six intensity levels, those levels are in the range 0 = absent, 5 = maximum. The AU43 is coded as 0 for close eyes and 1 for open eyes. The dataset provides 66 landmarks, they are used to compute the similarity normalized shape features (SPTS), and to reduce the landmarks' dimensionality, Principal Component Analysis is applied. 99% of the variance is kept this reduced the frame-level features from 132 to 29 dimensions. An example of different PSPI scores for the same subject is shown in figure 2 (Saha et al, 2016). In this paper, the UNBC dataset is used with AU_based method.

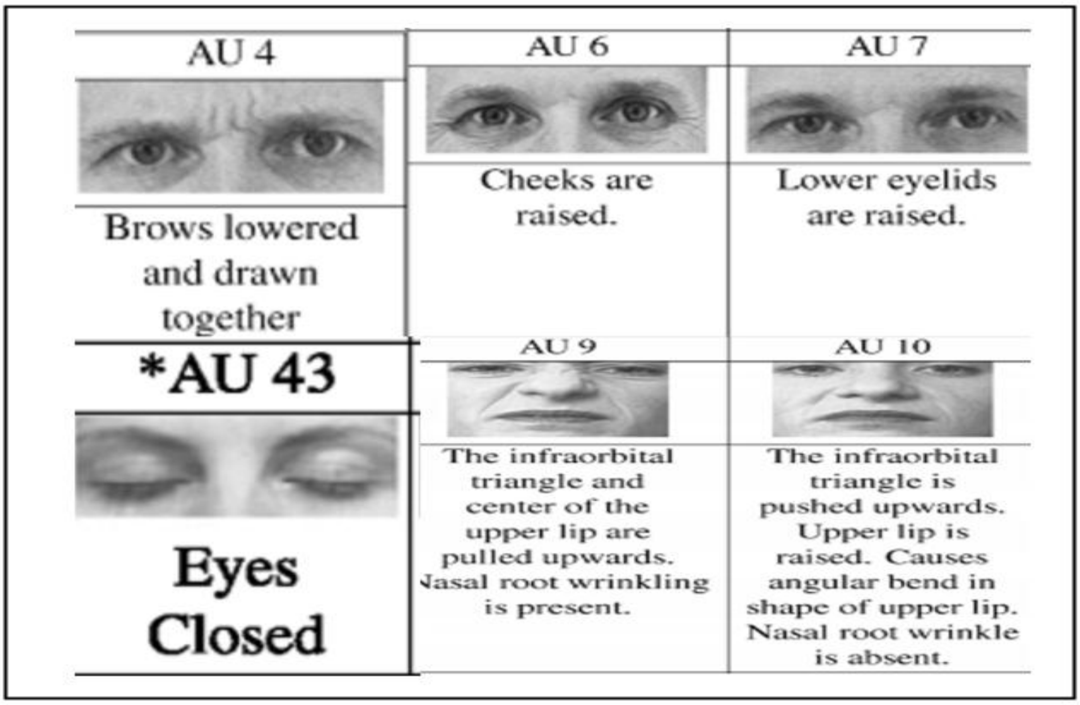

Figure 1: Action Units AUs that are used in PSPI scores appeared in equation 1

Figure 2: Sample of the same participant with different PSPI scores from UNBC_Mc Master dataset (Friesen et al, 2002)

3.PAIN DETECTION PIPELINE

In this section, the core technology utilized by the proposed system pipeline to detect pain is represented. First, an explanation of how the facial landmarks (features) are detected and tracked is provided. Second, a description of how these features is utilized to compute the Action Units AUs intensity. Finally, the Support Vector Machine classifier role is explained to classify the pain level of the patient in real-time.

In this paper, two methods are proposed to patient's detect pain level during the telehealth appointment. The first method named Active Appearance based methods AAM_based method, in this method, the facial features are extracted for modeling purpose for pain detection. The second method named AU_based method, in this method, the facial expression coding FACS is generally utilized for pain assessment.

The pain detection process starts by detecting the patient's face, crop it, and extracting the landmarks. The extracted features are used to find the region of interest ROI using the two proposed methods separately. For classification the Support Vector Machine classifier is used to detect the pain level for each method, and the results for each frame will be saved in a CSV file to and deliver to the physician for better treatment. Figure 3 shows the pipeline of the work proposed in this paper. Following is the mathematical model for the proposed method:

S= {∑, F, □, C}
S = Pain Detection
∑ = Set of input symbols = {datasets video, images, pain classes}
□ = 1 Start
2. Read dataset N*N
3. Resize image dimension N^2 *1
4. Select training set N^2 * M, M: Number of samples in the dataset

5. Extract 166 landmark using Active Appearance Model AAM
6. Apply Principal Component Analysis PCA
7. Apply Support Vector Machine SVM for classification
8. End

F = Set of output symbols = {pain levels PA0 (no pain), PA1, PA2, PA3, PA4 (highest pain), csv file}

A. Face Detection

In this stage, the person's face in each video frame is searched, cropped, and detected. By using Intel open-source framework known as OpenCV (Shervin Emami, 2010)), face detection is performed easily and reliably. The advantage of OpenCV is being a multi-platform framework; it is compatible with Linux, Windows, and Mac OS X. OpenCV provides many basic computer vision algorithms to use as a key for achieving a good facial detecting and tracking result. In this paper, several OpenCV modules are used such as CXCORE, CV, CVAUX, and CVCAM key namespaces.

In this section, the generation of the appearance model for the faces is explained. In each video frame, both models of the shape and appearance variation are combined in a normalized shape frame. To indicate the essential features, a training set of facial images with landmark points at interesting positions is required to create a statistical pattern of shape variation.

$$x = \underline{x} + P_g b_g$$

Where $\underline{x}$ the computed mean of shape model, P_g is the orthogonal variation modes, and b_g is a list of shape variables. The triangulation algorithm is used to generate the statistical model for appearance's grey level for

$$g = \underline{g} + P_g b_g$$

Where $\bar{g}$ is the ger-level normalized mean vector, P_g is a list of grey-level variation's orthogonal modes and b_g is a set of parameters for the grey-level model. P_g and b_g vectors are

$$b = Qc$$

Where c is a set of parameters for the appearance model that control the shaper and the model's grey level and Q are b's eigenvectors.

B. AAM_Based Method

Upon detecting faces using an OpenCV algorithm such as Haar cascade, AAM_based method an Active Appearance Model (Cootes and Taylor, 1994) was used as a statistical technique to match image templates. For the aim of finding parameters that reduce the discrepancy between the synthesized image and observed image, the AAM is used in this paper. AAM is a parametric model of both texture and shape, considered as the basis of efficient method to align an image's predefined template with the features of the face. The shape model is extended by n eigen shapes S_i added to the average shape S_0.

$$S = S_0 + \sum_{i=0}^{n} P_i S_i \qquad (2)$$

The facial landmarks 2D-points represent the shape of the face, these set of 2D-points is aligned into a spread co-coordinate frame and introduces as a vector, v by employing Procrustes alignment. After generating the features vector, a Principal Component Analysis PCA is utilized it using the following equation:

(3)

every video frame by matching the mean shape with landmark points. After normalizing the vector g to reduce the effect of maximum lighting variation. Then PCA is applied to obtain the linear equation:

(4)

symbolizing the appearance and any video frame generated using AAM. A further PCA is applied to the data to generate the concatenated vector and give a further model.

(5)

The selected list of eigenvectors Q are multiplied by the matrix c to create a reduced eigenface.

In this paper, a training sets Biovid and UNBC are utilized to build the facial appearance model. Each frame had 122 landmark points surrounding the main features. The shape model includes 23 parameters is generated. The shape model required 10,000-pixel points to create the facial patch.

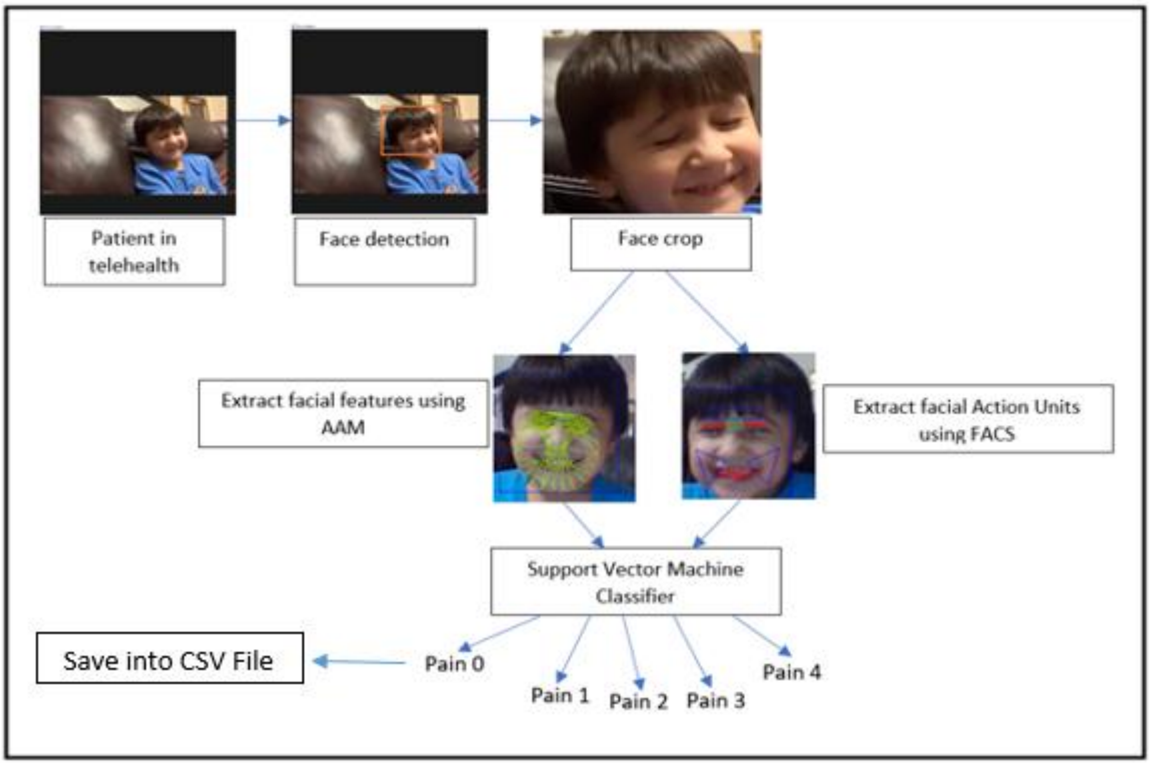

Figure 3: Pain detection system pipeline

C. AU_Based method

Many behavioral science studies show that human facial expression has a strong relationship with pain detection. The pain is encoded from the facial muscles' movement into a set of Action Units, depend on the coding system called FACS. Figure 4 shows a sample of some facial action units AUs 4, 6, 7, 9, 10, and 43 associated when the patient is in pain.

The four AUs in figure 4 were founded by Prkachain (Prkachin and Craig, 1995) considered as the four core actions linked to pain and they contained most of the pain input data. These actions defined the patient's pain by adding the intensities of lowering the eyebrow (AU4), tightening the orbital (AU7 and AU6), elevator contraction (AU10, AU9), and closing the eyes (AU43) as shown in equation 1 that calculates PSPI.

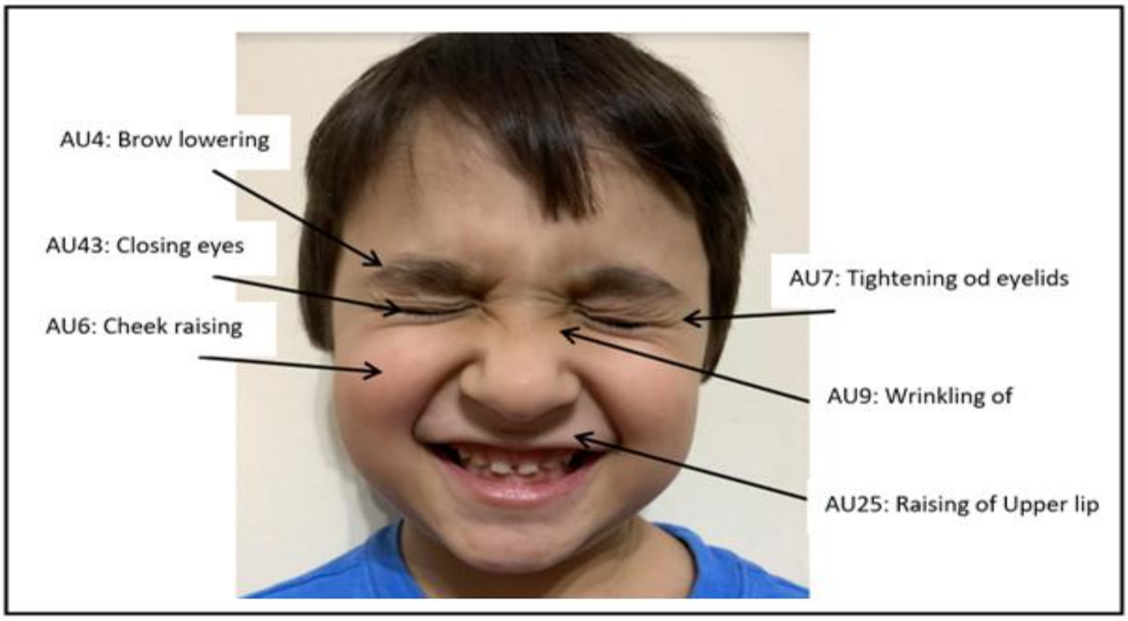

Figure 4: An example of facial action units AUs for a patient in pain level 4

Equation 1 uses to detect PA4, in this paper combination of action units AUs are used to compute the other pain levels (PA1, PA2, and PA3) as shown in table 1. AU1 represents a contribution to emotions such as surprise, sadness, and fear with a frontalis muscular basis. AU15 represents a contribution to sadness and disgust emotions with underlying facial muscle. AU23 represents a contribution to anger with an orbicular orris muscular basis. AU24 represents a contribution to affective anger emotion with an underlying facial muscle. The three computed pain levels are added to the dataset and a classifier are trained and tested to predict the patient's pain level during the telehealth appointment.

Table 1: The pain equations for each level

PA	AUs	Emotions
PA1	AU1+AU15	Surprise + Sadness + Fear + Disgust
PA2	AU1+AU6+AU23	Surprise + Sadness + Fear + Anger + Happiness
PA3	AU4+AU6+AU24	Anger + Happiness

D. Support Vector Machine

SVMs have been used as a classifier for many patterns recognition tasks such as facial action recognition. In this paper, the SVM classifier is used for detecting pain from a patient's facial actions because it is the best suited binary classifier for this task. The main season to select SVM as a classifier in this paper is to generate a sizeable volume of training samples and construct the compact discriminative model automatically. For a specific class, SVM found the hyperplane that increases the negative and positive observations margin. The decision of the linear SVM classifier is obtained for an observation X^* by the following equation:

$$W^T X^* \begin{array}{l} > \mathrm{b}\ True \\ < \mathrm{b}\ False \end{array} \qquad (6)$$

Where w is the vector that separates the basis b and the hyperplane.

4.FINDINGS

To evaluate the proposed system two sets of experiments are devised. The first experiment was conducted on method 1 that detects the patient's pain in each video frame using pain intensity. The second experiment was conducted on AU_based method that detects pain using a patient's facial actions.

A. Environment

A laptop with the following configuration is used to conduct all experiments in this paper: 2.3 GHz Intel Core i7, 0.92 megapixels for still image, and 1280x720 (HD) for video at 30 fps and 16 GB RAM.

B. AAM_Based Method Results

The Biovid database is used to test the performance of AAM_based method. The facial features from each frame utilized as inputs to the SVM classifier. The output scores produced by SVM determine the pain level in each video frame. The results of applying AAM_based method on ten samples of the Biovid dataset are shown in figure 5. The data results contain a pain level from each frame is saved in a csv file for further research usage. As shown in figure 5, pain L0 and pain L4 have the highest accuracy rate. The precision for pain is 78% for AAM_based method.

C. AU_Based Method Results

To test the performance of AU_based method, the UNBC dataset is used. The AUs are utilized as baseline input features to the SVM classifier, The SVM used a grid search to find the best parameters for pain detection. The results show that the precision for pain is 89.3%. In figure 6, the results of detecting pain for ten UNBC video samples show that pain level-0 and level-4 have the highest accuracy rate. Figure 7 shows the result of implementing the proposed system on sample 1 of the Biovid dataset. In the figure the pain levels are represented in the source code as PainLV0, PainLV1, PainLV2, PainLV3, and PainLV4 and they are equivalent to PA1, PA2, PA3, and PA4 in this paper respectively. Where PainLV0 is the baseline level indicates no pain and PainLV4 indicates highest pain level. As mentioned before in section 3, the UNBC dataset includes only two pain levels; PA0 (no pain) and PA4 (pain as bad as could be) and in this paper the other three pain levels PA1, PA2, and PA3 are computed, added to the dataset to help in training procedure and improve the outcome during the testing stage.

D. Results Comparison

In table 2, these results of AU_based method are compared with Lucey et al, and Sikka et al, both methods used UNBC pain dataset to evaluate their proposed methods. Lucy et al. used three pain classes (PA1-0, PA2-3, PA4-5) to group all samples in the UNBC dataset and extracted the canonical normalized appearance features (CAPP), while Sikka et al. used two classes (PA 0 and PA 3-5). The experiment was conducted with both variants and different frame-level features. The accuracy which indicates the number of samples that correctly classified divided by the total number of samples. The AU_based method outperformed the other methods by using simple linear SVM, which proved the superiority of the AU_based method's temporal integration. Comparing the three methods regarding the different frame - level features observed that the AUs-based method's shape performed better with the appearance features than the Lucey et al. and Sikka et al.

Table 2: Comparing AUs_based method with other similar methods

Method	Frame-level features	Classifier	Accuracy
Lucey et al.	SPTS + CAPP	SVM	0.610
Sikka et al.	Dense Sift BoW	MS-MIL	0.837
AU_based proposed method	SPTS (PCA + 29 dim)	SVM	0.893

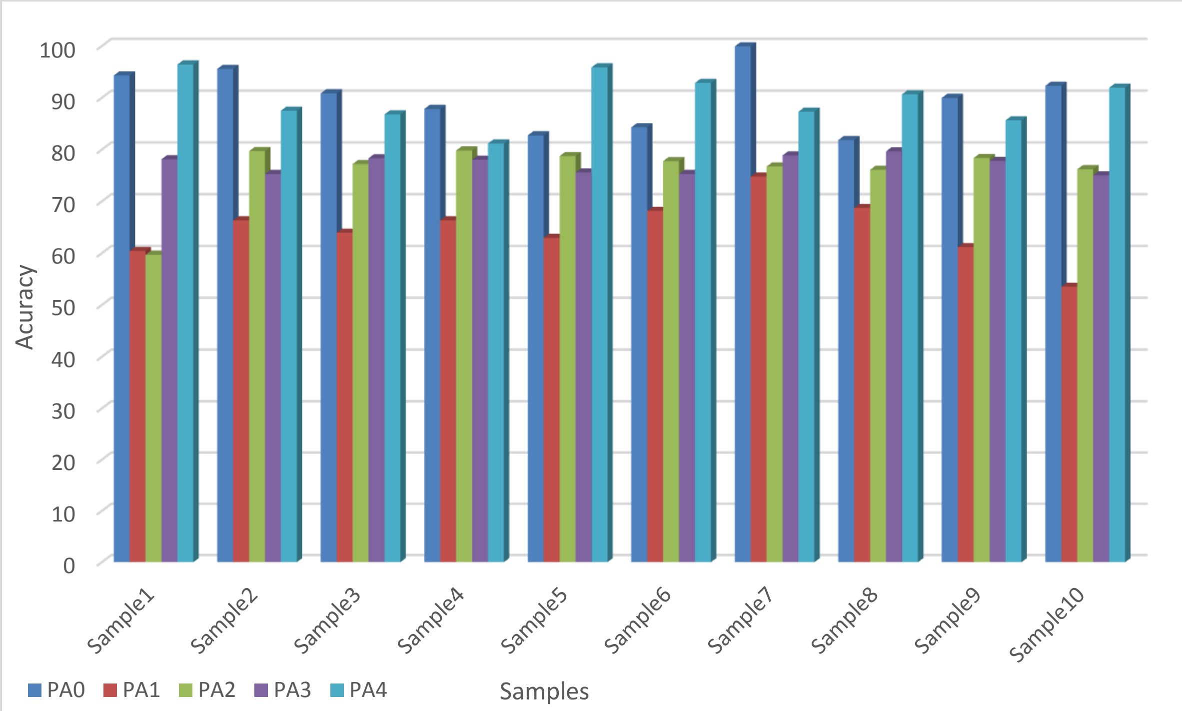

Figure 5: The result of performing the AAM_based method on 10 Biovid dataset video samples

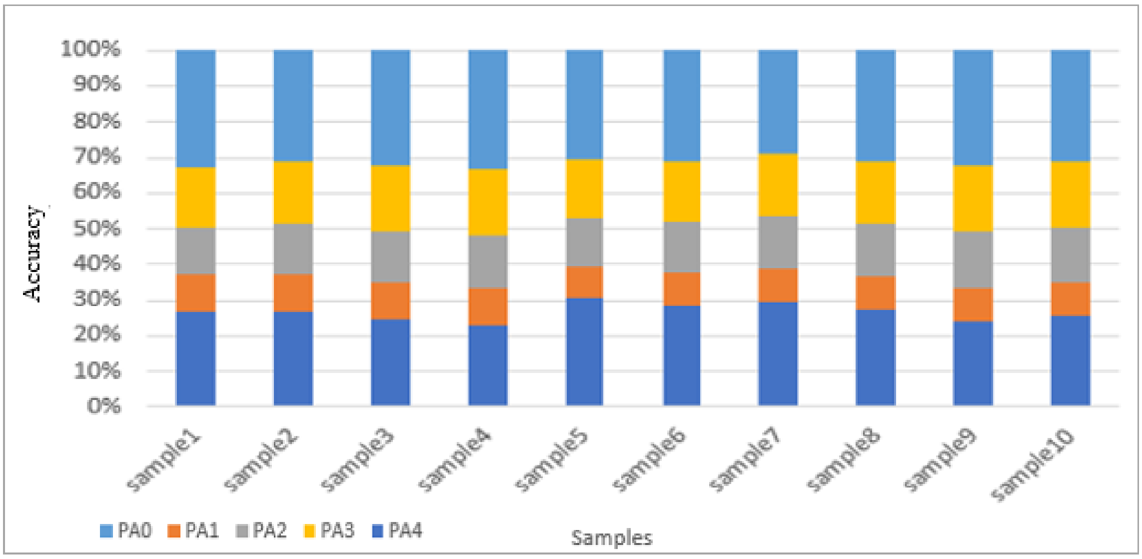

Figure 6: The result of performing AU_based method on 10 UNBC dataset video samples

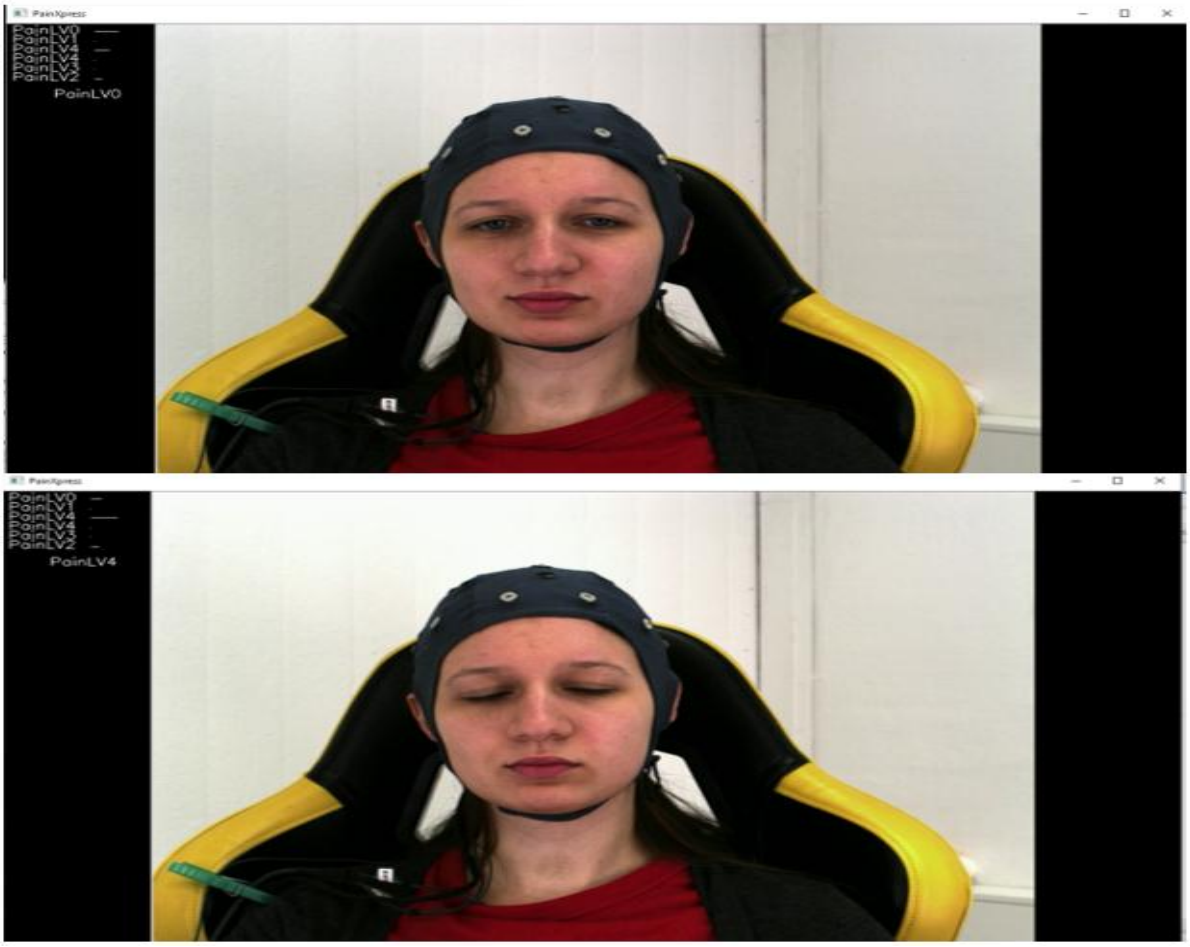

Figure 7: The result of implementing the proposed system on the Biovid video dataset

5.CONCLUSION

In this paper, a real-time pain recognition system based on the patient's facial expression during telehealth is proposed. The proposed automated system detects the patient's pain during telehealth using two approaches based on the patient's facial expressions. AAM_based method uses the extracted facial features directly to detect the level of the pain, while AU_based method uses a set of AUs to detect the pain levels. Two databases are used to test the performance of the developed system. These two datasets are UNBC which includes patients with shoulder pain and Biovid which uses heat to induce subjects with four pain intensities. These datasets missing several facial expressions that lead to minimizing the accuracy of the proposed method. Extract facial expressions from the video sequences such as anger, surprise, and sadness are added to the training datasets. The added emotions lead to add more AUs to AU_based method such as AU12, AU25, and AU20 to compute the different pain equations. Adding extra facial emotion increased the accuracy for the proposed system from 66% to 78% in AAM_based method and from 70% to 89.7% in AU_based method. The results of evaluating the system's performance indicated that in both methods the proposed system able to detect PA0 (no pain) and PA4 (high pain) more accurately compared with other pain levels.

In future research, a plan to include head movement, eye gaze, body movement, and audio will be examined to improve the performance of the proposed automated pain detection system which will be also a useful framework to detect depression emotions.

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