JOURNAL OF NANO- AND ELECTRONIC PHYSICS | *ЖУРНАЛ НАНО- ТА ЕЛЕКТРОННОЇ ФІЗИКИ*
Vol. **16** No 5, 05018(5pp) (2024) | Том **16** № 5, 05018(5cc) (2024)

REGULAR ARTICLE

Artificial Intelligence-Based Pain Intensity Detection through Facial Expression Analysis

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(Received 09 June 2024; revised manuscript received 14 October 2024; published online 30 October 2024)

Recognizing emotion expression has become more difficult in recent years due to significant variation. Pain intensity detection using ML involves leveraging algorithms to analyze various indicators, viz. facial expressions, physiological signals, or behavioral patterns, to objectively assess and categorize the severity of pain. ML models, trained on diverse datasets, enable accurate predictions and contribute to advancing non-invasive and automated approaches for evaluating pain intensity in clinical settings. This paper survey the different models that have been used by researchers in last few years and the accuracy achieved by them in various pain datasets used in their existing literature. It also suggests a general framework idea for a system that opens the door for individualized, data-driven treatment plans in addition to providing healthcare professionals with fast and accurate diagnostic information. The limitations of traditional methods, which often rely on subjective self-reporting, especially when dealing with patients who are unconscious or partially abled and unable to communicate verbally, are recognized in our research. Such type of designed system can excel in detecting pain sentiments by closely examining facial expressions, providing a valuable non-verbal avenue of communication for individuals who face challenges in articulating their pain verbally. The opportunity for IoT and cloud computing to transform healthcare by offering a real-time, non-invasive way to measure pain intensity have been suggested in this paper.

Keywords: ML, Healthcare, IoT, Cloud computing.

DOI: 10.21272/jnep.16(5).05018 | PACS number: 07.05.Tp

1. INTRODUCTION

Pain is described as "an unpleasant sensory and emotional experience associated with actual or potential tissue damage, or described in terms of such damage" by the IASP. Social responses like empathy, caring, and nursing are triggered when someone expresses pain [1]. For this reason, it's critical to identify pain early and treat it appropriately. Self-reporting techniques cannot be used by patients those who are not able to communicate because of a serious illness, opioid medication, cognitive impairment, or early infancy [1]. Consequently, it is essential to have assessments from other individuals, particularly careers and nursing staff. Fig. 1 shows a generalized flow to detect the pain intensity of the patient using clinical data.

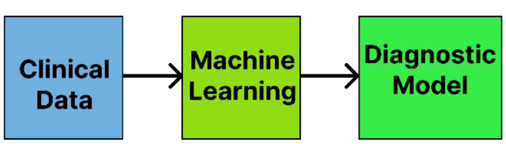

Fig. 1 – General block diagram showing the flow of clinical data, ML, and diagnostic [1]

This novel method uses Internet of Things (IoT) devices with strategically placed, high-resolution cameras to record patients' in-the-moment facial expressions while they are in pain. These devices produce data, which is seamlessly transferred to a centralized cloud computing infrastructure for processing, analysis, and storage. The cloud-based platform utilizes sophisticated machine learning algorithms and facial recognition techniques to derive valuable insights from the gathered data. Cloud computing makes scalable and effective data storage possible, guaranteeing that medical professionals in various locations can access patient information [2]. Furthermore, by incorporating machine learning models into the system, it becomes possible for it to learn from and adjust to the unique nuances of each patient, eventually increasing the precision of the diagnosis of pain intensity.

By integrating computerized and mobile healthcare facilities, a new age of technology viz. cloud computing [2] and IoT as shown in Fig. 2 has improved the healthcare sector. The Mobile-Health system in smart cities provides patients with daily medication support, and as technology advances, both electronic and mobile health are supporting e-Healthcare systems. In order to create a healthy society in smart cities, these e-Healthcare systems are beneficial to all the medical experts, physicians, patients, and enterprises [3]. Artificial Intelligence (AI) has emerged as an ally for IoT in this emerging environment. Hospitals, telemedicine,

Cite this article as: U. Rawat et al., *J. Nano- Electron. Phys.* 16 No 5, 05018 (2024) https://doi.org/10.21272/jnep.16(5).05018

medical equipment, and healthcare professionals are only a few of the many various sectors that makes the healthcare industry, a significant contributor to employment globally. Welcome to a new era enhanced by electronic and mobile health services that make healthcare available in smart cities. All parties involved – doctors, nurses, patients, and businesses – are now better equipped to build savvier, more intelligent communities [3].

1.1 Sentiment Analysis

Using facial expression recognition analysis, this review intends to help the researchers to create a Pain Intensity Detection System (PIDS) that can measure patients' degrees of pain. This PIDS will improve the features of the e-Healthcare system, facilitating doctor and nurse decision-making. With the use of AI and a person's facial expression, this PIDS framework idea will enable the analysis of pain severity utilizing the person's emotions [4]. For delivering true patient care and assessing its efficacy in the clinical setting, the pain analysis is essential. A patient's behavioral awareness, particularly the use of facial expression, is thought to be the most important behavioral pointer of pain. This is true when the capacity of the patient to convey their pain get compromised. Patients who are near to death, rationally paralyzed, severely ill and composed, or who are experiencing mental decline, brain realignment or head and neck cancer are particularly frail and require technological devices to deliver reliable and authentic signals about their agony to busy psychoanalysts [5].

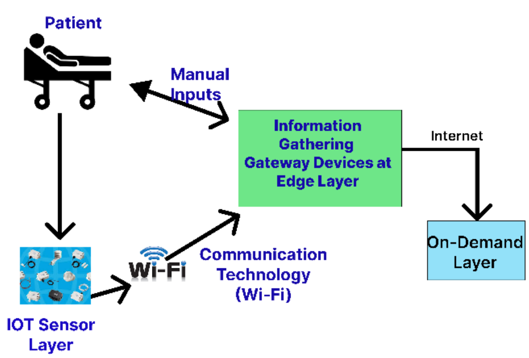

Fig. 2 – Integration of IoT devices and CC in diagnosing the patient [2]

Observational methods of measuring pain are extremely difficult and influenced by the observer's subjective biases and false beliefs. Furthermore, it is not feasible for human careers to keep a patient under constant observation. The result of all these factors is inadequate pain management. One of the reliable markers of pain is facial expression, which can be found in the observational scales used to measure pain. considering that patients who are incapable of reporting pain on their own, such as infants, critically ill adults with cognitive impairment, or unconscious patients in an ICU, automatic systems may be more reliable and objective methods of diagnosing pain than human observers.

According to Othman et al. [4], when it comes to analyzing frontal faces in videos, machines are far more proficient than humans at identifying the degree of pain. Alghamdi et al. [5]. Designed a system that records the incident, the patient's pain level, date, and time, and alerts medical personnel when a patient experiences pain. Two convolutional neural networks that have already been trained, either ResNet50, InceptionV3, VGG16, or ResNeXt50, are used by the subsystems to extract the pertinent input features. All convolutional blocks are frozen, and a shallow CNN is used in place of the classifier layer.

The Prkachin and Soloman pain intensity (PSPI) equation can be used to calculate pain by giving values in numbers for those six AUs, as illustrated below [5]:

"PSPI = AU4 + max(AU6,AU7) + max(AU9,AU10) + AU43"

Based on a range of 0 (without pain) to 16 (Highest pain pain), the PSPI score indicates the degree of pain as depicted in Fig. 3. Fig. 4 shows the intensity of the PD based on three categories strong pain, weak pain and no pain.

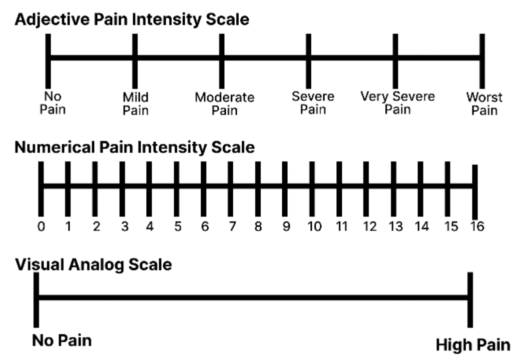

Fig. 3 – Pain Intensity Scale [5]

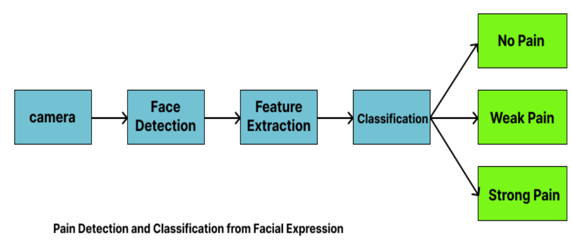

Fig. 4 – General PD flow diagram based on three categories of pain [1]

The eyes/brow region and the entire face, are generally utilized as input images for the model. [18] There are various methods to evaluate pain, the most effective being consultation with a specialist physician. Therefore, it might be necessary to have multiple physicians with different specializations present to determine the patient's pain level. For instance, in certain patient cases, the therapist requires the assistance of a team or a specialist physician to assess the degree of pain; this is an expensive and time-consuming task that is not always accomplished. This method's primary drawback is its poor accuracy.

AI/ML use in pain assessment has expanded to include the merging of physiological and demographic data with information from facial expressions. Some studies have also used automated PD algorithms on young patients undergoing laparoscopic appendectomies. Their findings demonstrated improved clinically relevant PD when electrodermal activity and facial expressions were integrated as input. Furthermore, a number of studies have demonstrated the ability to improve the precision of pain identification by integrating information on facial expressions with bio-physiological and demographic factors, including skin conductivity, electromyography, and electrocardiograms.

2. BACKGROUND AND STANDARD PIPELINE STRUCTURE FOR PIDS

Describing the standard pipeline algorithm for facial expression based pain recognition as shown in Fig. 5. From the implementation point of view, the process starts with collecting of pain-related face expressions data and analyses it for the intensity of the pain. In the context of pain intensity detection using facial expression analysis, several key components make up the process, that include. [5]:

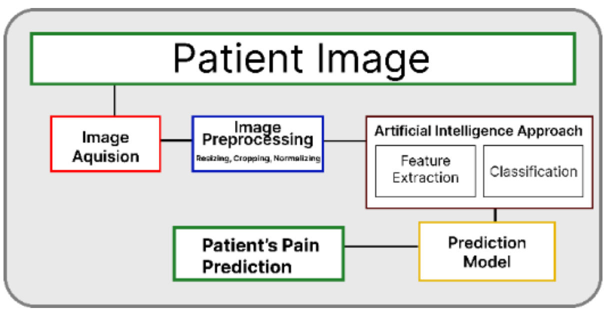

Fig. 5 – Healthcare Frame work for pain Intensity Detection System [1]

Image Acquisition: It refers to the capture of live or recorded video sources that contain pictures or frames of a person's face. In real-world applications, this stage frequently calls for the use of cameras, video recording equipment, or even picture databases.

Image processing: Image processing is the process of modifying, improving, and preparing obtained face pictures for analysis. During this phase, it's typical to do activities like face alignment and detection, noise reduction, lighting and color normalization, and standard picture scaling. The objective is to guarantee consistency and the absence of any artefacts that can obstruct feature extraction.

Feature Extraction: Identifying and measuring particular face characteristics or patterns that are essential for determining pain severity is known as feature extraction. To characterize the changes in facial shape and appearance brought on by facial expressions, features are taken from facial images and image sequences. In order to extract a collection of characteristics, facial markers like the eyes, nose, mouth, and other areas are found. The separation between face landmarks, angles, texture data, and statistical evaluations of pixel values are a few examples of these traits. The most informative characteristics may be found by using feature selection strategies.

Classification: Classification is the process of categorizing or classifying an input picture based on the features that have been retrieved. Images are categorized according to their level of discomfort using ML techniques, such as neural networks, decision tree, Support vector machines or DL models, which are trained using labelled data. The study objectives, as well as the caliber and volume of information at hand, all influence the classifier that is selected.

Prediction Model: To assess pain intensity from facial expressions, the prediction model is the comprehensive framework that combines all of the above processes. The core component of the prediction model is the trained classification model. To forecast the amount of pain intensity, brand-new, previously processed photos are run through the algorithm. A categorical designation or a numerical score might be the forecast.

The efficient execution of these elements is crucial for the effectiveness of pain intensity identification using facial expressions. The accuracy of the model, the resilience of the image processing methods, the in formativeness of the extracted features, and the model's overall prediction abilities are all crucial to the system's performance and dependability.

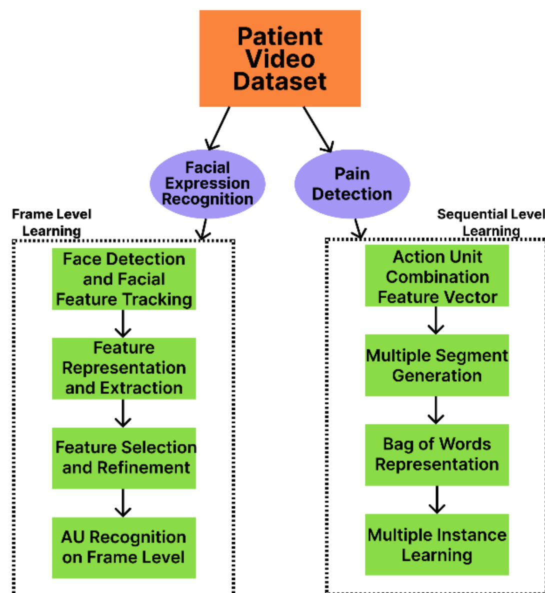

Fig. 6 – Decoupled PD Framework

Numerous factors, including tools for feature extraction, ML algorithms, video or image quality, cross-validation techniques, data processing techniques, and others, differ significantly across studies investigating facial expression-based pain intensity detection. Each model's performance and efficacy might be considerably impacted by these variances.

It is noteworthy that research using the same people and various approaches have differing degrees of success. The selection of feature extraction methods also turned out to be a crucial element affecting model correctness [6]. According to several research, different feature extraction methods combined with same classifiers resulted in different degrees of accuracy when detecting pain severity.

3. METHODOLOGY

The primary method used to gather peer-reviewed papers was looking through digital libraries like IEEE Xplore3, and ScienceDirect5. The following search terms were used: “pain intensity estimation,” “pain intensity detection using facial expression”, "automatic facial expression based pain detection," "facial expressions of pain," and "automatic pain recognition." Only articles that incorporated facial expression data from images or videos were taken into consideration. Paper objective, dataset(s), and direct or indirect extracted feature representations from the visual input were focused during literature review. Table 1 shows the literature review of the recent work.

In 2024, B. Sowmya et. al. designed a system that can simultaneously perform face recognition and emotion classification. Based on classifier output, a visualization technique is applied to differentiate between various emotions. The mini-Xception algorithm successfully completed all tasks, including emotion recognition and classification [7].

In 2024, Á. Sabater-Gárriz et. al., study shows how DL models can be used to reliably detect pain in people with neurological disorders and communication impairments [8].

Table 1 – literature review of the recent work

Ref.	Year	Model/Method	Accuracy / Result	Dataset Used
[7]	2024	mini-Xception algorithm	accuracy of approximately 95.60%.	FER-2013 dataset
[8]	2024	InceptionV3	an accuracy of 62.67% and an F1 score of 61.12%	CP-PAIN dataset
[1]	2023	cutting edge techniques	Computes scores for intensity of pain	UNBC-McMaster shoulder pain and 2D Face-set database
[9]	2022	Shutter blinds-based	More than 95% overall accuracy	UNBC-McMaster Shoulder Pain
[10]	2022	Combination of 16 tested model	Optimal model accuracy = 99.10% on 10-fold cross-validation also scored 90.56% on unseen subject data	UNBC-McMaster Shoulder Pain
[11]	2022	Fine-tuning a DL model	Average Precision (AP) = 72% and AUC = 82%	video dataset gathered from patients' masked faces during sedation-assisted medical procedures
[12]	2022	YOLOv5	Accuracy = 68.7%,	USFMNPAD-I
[13]	2021	Off-the-Shell CNN architectures	Accuracy (unbalanced) = (99.665%, Accuracy (balanced) = 95.44%	UNBC-McMaster Shoulder Pain
[14]	2021	RFc and two-CNNs	outperformed human observer by 6% and 7%, respectively.	X-ITE
[15]	2020	Temporal Convolutional Network (TCN) And long short-term memory (LSTM) model	AUC = 85% and Acc. = 92.44%	UNBC-McMaster Shoulder Pain and MIntPAIN databases
[16]	2020	EJH-CNNBiLSTM	AUC = 98.4% and test accuracy = 90%	UNBC-McMaster Shoulder Pain
[17]	2020	Ensemble DL Model, EDLM)	Feature classification accuracy = 89 % Receiver operating characteristic = 93 %.	UNBC-McMaster Shoulder Pain

4. CONCLUSION

This paper presents a review of sophisticated Pain Intensity Detection system(PIDS) including its features, tailored for PD within the context of a smart healthcare framework. Recognizing the limitations of traditional methods reliant on subjective self-reporting, especially in cases where patients are unconscious or partially abled and unable to communicate verbally. This review will help the researchers to design a system which would be helpful in detecting pain sentiments, providing a valuable non-verbal avenue of communication for individuals facing challenges in articulating their pain verbally.

5. FUTURE SCOPE

1. **Integration of IoT for Pain Intensity Detection**: The incorporation of Internet of Things (IoT) technology could enable real-time monitoring and enhance the precision of pain assessment.
2. **Empowering Cloud Computing for Remote Monitoring**: The system's capabilities can be empowered by integrating CC, allowing for remote monitoring from any location and at any time.

3. **Need for Diverse and Ecologically Valid Datasets**: Addressing the challenge of pain and negative emotions often being confused requires the development of datasets containing real-world scenarios with both pain and emotions as control conditions.

4. **Efficient Computation for Mobile Devices**: developing algorithms that operate efficiently on low-processor devices, particularly mobile phones.

5. **Addressing Variability in Pain Tolerance**: Recognizing the variability in pain tolerance among individuals, considering factors such as age and gender, poses a challenge.

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Виявлення інтенсивності болю за допомогою аналізу виразу обличчя використовуючи методи штучного інтелекту

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Останніми роками розпізнавання вираження емоцій стало важчим через значні варіації. Виявлення інтенсивності болю за допомогою ML передбачає використання алгоритмів для аналізу різних показників, а саме. вираз обличчя, фізіологічні сигнали або моделі поведінки, щоб об'єктивно оцінити та класифікувати тяжкість болю. Моделі ML, навчені на різноманітних наборах даних, дозволяють точно прогнозувати та сприяють вдосконаленню неінвазивних та автоматизованих підходів для оцінки інтенсивності болю в клінічних умовах. У цій статті розглядаються різні моделі, які використовувалися дослідниками протягом останніх кількох років, і точність, досягнута ними в різних наборах даних про біль, які використовуються в їхній існуючій літературі. Він також пропонує загальну рамкову ідею для системи, яка відкриває двері для індивідуальних, керованих даними планів лікування на додаток до надання медичним працівникам швидкої та точної діагностичної інформації. У нашому дослідженні визнаються обмеження традиційних методів, які часто покладаються на суб'єктивну самооцінку, особливо при роботі з пацієнтами, які перебувають у несвідомому стані або частково недієздатні та не можуть спілкуватися вербально. Такий тип розробленої системи може досягти успіху у виявленні відчуття болю шляхом ретельного вивчення виразу обличчя, забезпечуючи цінний невербальний спосіб спілкування для людей, які стикаються з труднощами у словесному вираженні свого болю. У цій статті було запропоновано можливість для IoT і хмарних обчислень трансформувати охорону здоров'я, пропонуючи неінвазивний спосіб вимірювання інтенсивності болю в реальному часі.

Ключові слова: ML, Охорона здоров'я, IoT, Хмарні обчислення.