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BINARY PAIN DETECTION USING FACENET FOR FEATURES EXTRACTION

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Abstract

Signs of pain, generally, could be detected from facial expressions. Facial monitoring is vital to measure pain because it is relatively easy to be noticed and accurate. Recently, deep learning has been used to look at the use of facial expressions and movement to sense pain. A dataset from the University of Northern British Columbia (UNBC) were used in this paper to train the model. This research proposes a mechanism to detect the pain. It classifies the facial expressions into two categories: painful and non-painful. Two models of the collected data were dealt with. The first was balanced (that is the two groups of data are of nearly equal size) and the second was unbalanced. The feature extraction of the whole dataset was done with Face Net followed by a fully connected neural network. After training the model, the accuracy of the unbalanced data was (99.665%), while it was for balanced data with a value of (95.44%). In summary, this paper introduces an alternative technique developed to detect the pain. The method is straightforward, cost-effective, and easily recognizable by both public and healthcare professionals.

Keywords: Facial Expression, Face Recognition, Machine Learning; Pediatric Pain, Facial Action Coding System.

1. INTRODUCTION

Everyone experiences pain from time to time at extremely excessive levels. Pain can be assessed in several ways, the best of which is traditionally through a specialized doctor, so it may require the presence of more than one doctor with more than one specialty to assess the extent of pain in the patient. for example, when the therapist work on some cases of patients he needs to a specialist doctor or an entire team to determine the extent of the pain, and this is a matter that requires high cost and time and cannot always be obtained. The self-classification strategy [1] was used with the help of many patients and health care experts to measure the severity of their discomfort [2]. The main downside of this method is its lack of accuracy. Pain can be viewed in a completely different way with the help of sufferers and scientific specialists, especially in children [3]. The Observer Rating Scale (ORS) was used as a follow-up to the self-report strategy in order to help humans increase its accuracy [4].

Pain can have many unique sources, which include sore throats, shoulder injuries, and belly pains. Therefore, even when different assessments of ache may additionally be

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accessible, in reality reporting a patient's situation is inadequate to acquire a correct treatment [5]. There are various techniques for evaluating pain, consisting of diagnostic and neuroimaging methods, however these remedies are pricey for the patients. Using facial recognition, in particular the Facial Action Coding Scheme (FACS), which acknowledges facial expressions, is one feasible option [6].

Forty-four motion gadgets Action Units (AUs) are used by means of the FACS visualization device to show facial muscle activity. This approach to useful resource human beings in figuring out human emotional states like melancholy, anger, impartiality, and calm has been notably studied [7][8]. Lucey et al. [3][9], Prkachin and Solomon [10][11], who brought FACS to the scientific neighborhood initially, proposed the Prkachin and Solomon Pain Intensity (PSPI) meter [12]. FACS, which usually identifies ache the use of facial muscle tissue and codes them the use of the applicable AUs, can be used by means of PSPI to measure pain. Every AU is scored on a dimension of zero to 5, with the exception of AU43, which has two characteristics (0,1). They seem facts in this find out about has been extricated from the UNBC, a vast aggravation acknowledgment dataset. Nonetheless, torment ranges are conflicting throughout the UNBC [13].

Prkachin and Solomon [10][11] encouraged the PSPI. In their review, torment demeanor used to be absolutely characterized via the enactment of a limited association of facial muscle groups and coded by means of a nearby vicinity of associated AUs: AU4, AU6-AU7, AU9-AU10, and AU43. The PSPI metric is added in stipulations 1 and 2 [9]:

$$PSPI = AU4 + max\ (AU6 - AU7) + max\ (AU9 - AU10) + AU43 \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots \ (1)$$

$$Pain = intensity\ (AU4) + (max\ intensity\ AU6, AU7) + (max\ intensity\ AU9, AU10) + intensity\ (AU43) \ \ldots\ldots\ldots\ldots\ (2)$$

This examination capability to introduce a 3D framework for figuring out and ordering facial torment that utilizations AI and improvement strategies, explicitly improvement innovation that approves human beings to hold a serious stage of route whilst altering from one facet to the next [14]. This comes from the framework's ability to foresee the hub of the decoded photo in mild of instructions from a reference picture. Our middle commitments are as per the following:

- A methodology for recognizing torment in view of AI for characterization and acknowledgment.
- Classification of pain into two categories: not painful, and painful.

A two-level scale used to be carried out due to the longing to make a approach that should be utilized as a popular machine for estimating torment in everyday day to day existence. The penalties of the examination matched the floor reality records of scientific experts.

The dataset that is used in this work was UBNC- McMaster in this dataset that is depend on the shoulder pain for 25 patients, which encompassed disorders like arthritis, bursitis, tendinitis, subluxations, rotator cuff injuries, impingement syndromes, osteoarthritis,

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capsulitis, and dislocations, served as the criteria for inclusion. Two distinct actions are captured: (1) the person moves his arm independently, and (2) the physiotherapist moves the patient's arm [15].

Although just one arm is painful, movements of the second arm and a control set are also recorded. There were recorded 200 sequences with 25 subjects (in total 48,398 frames). Except for AU 43, which is binary, the intensity values for the pain-related AUs 4, 6, 7, 9, 10, 12, 20, 25, 26, and 43 are reported for each frame on a 0–5 discrete intensity scale. A small portion of the data that was labeled by all three coders was able to achieve an inter-observer agreement of 95% (according to the Ekman-Friesen formula). The AU labels were produced by one of three professional FACS coders. The database's designers also include distinct pain intensities using the Prkachin and Solomon approach in addition to the AU notes [11].

In these types of works there is two ways to detect the pain from images the first way that is used deep learning by give the machine a huge number of pictures labeled pain and no pain then build a deep network and train it to suggest the result, another way by extract features of the images and train an ANN network on these features then compare the result with the Ground Truth of our images.

2. LITERAL REVIEW

In 2011, Lucey et. al., Describe the UNBC-McMaster Archive for Expression of Shoulder Pain, Use AAM/SVM Networks Pain detection is a key utility in which facial expression focus can be correctly applied, mainly if utilized in the context of a quite restrictive scenario such as an ICU ward the place the quantity of expressions is generally limited. [16].

In 2014 Piekartz & Mohr Provide a model for assessing somatosensory changes resulting from poor emotional processing. Progressive kinematics should be used in conjunction with manual therapy, exercises[17].

In 2017 Daniel Acevedo et. al. by modifying a k-Nearest Neighbors classifier called Citation-kNN, where the training examples are sets of feature vectors, these descriptors are tested for face expression identification. On the CK+ data set, comparisons with various cutting-edge technologies are displayed[18].

In 2017 Shier & Warren Adam created tools for automatically recognizing pain from facial expressions. Two fully automated systems are described, one utilizing convolutional neural networks, a sort of deep learning, and the other using Gabor filters with support for Vector Machines [19].

In 2018 Chen et. al., the similarities at the framework level between autonomic AFER and APD issues were highlighted in a review of research advances that contributed to automated pain detection [20].

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In 2019, Tavakolian & Hadid Develop a novel framework to capture variations in facial expressions for accurate pain intensity identification using CNN [21].

In 2020 Nour et. al., study three models for the creation of a facial expression recognition (FER) system that is built on deep convolutional neural networks. Alex-net, VGG-16, and Res-Net models are evaluated by the suggested method using CNN models with an SVM classifier[22].

In 2021 Andersen et. al., learning of a recurrent neural network, focuses on vast volumes of video data with ground truth rather than the extraction of video characteristics and representations. Initial findings amply demonstrate the significance of dynamics for pain perception and demonstrate [23].

In 2021 Morabit et. al., compared several popular and unofficial CNN (Convolutional Neural Network) architectures, such as MobileNet, GoogleNet, ResNeXt-50, ResNet18 and DenseNet-161. Both standalone mode and feature extractor mode have been applied to these networks. [24].

In 2021 Saddam et. al., This study will significantly support researchers' efforts to broaden the use of facial expressions to gauge patients' discomfort [4].

In 2020, Zhou et. al., Create a framework for group deep learning that combines a tailored hybrid deep neural network with a convolutional neural network (CNN) to extract characteristics from facial images and precisely detect and classify pain [25].

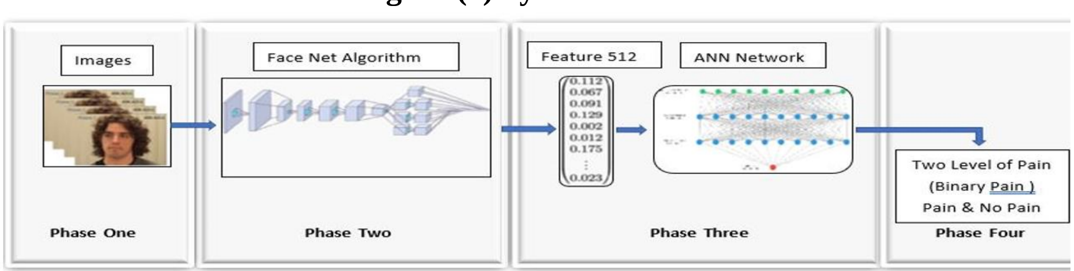
In 2022, Atee et. al., These findings deepen understanding of how PLWD portray clinical pain, and they support the value of real-time face analysis powered by artificial intelligence (AI) for pain assessment in geriatric clinical practice [26].

3. METHODOLOGY

The devolvement environment of this research was colab [27] including many libraries such as Numpy, Scipy, Pandas [28]. The facial pain dataset **(UNBC-McMaster)** was used [3]. The system was divided into four phases as shown in Figure (1).

Phases are: data collecting, features extraction, training with fully connected neural network and finally getting the pain/no pain prediction.

Figure (1) System Architecture



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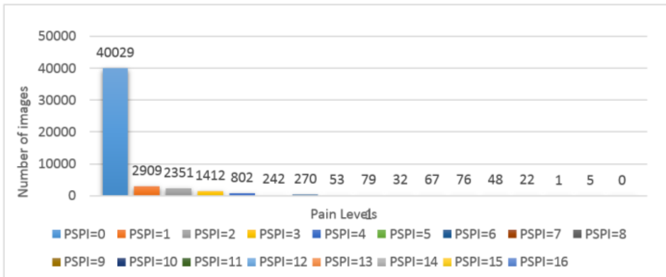
Data Collection phase

In this research, the well-known UNBC-McMaster dataset used, which contains 48,392 images taken of 25 different people and categorized into 15 pain levels, with the dimensions of each image in this database being 320*240. As show in Figure (2) showing the distribution of images in the original database as it is.

Figure (2) showing the distribution of images in the original database



The dataset separates into two kind the first Balanced Binary Pain Dataset (BBPD) and the second Unbalanced Binary Pain Dataset (UBPD) as shown in the figure (3) and figure (4)

Figure (3) new dataset BBPD

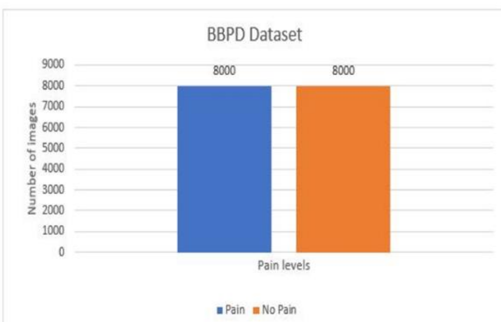
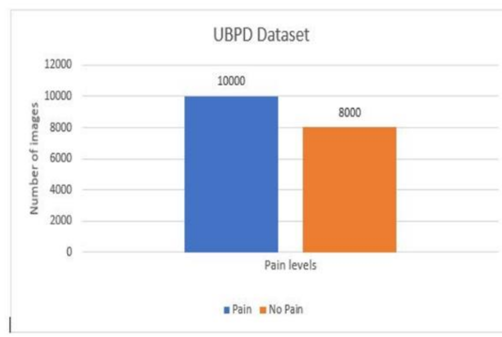


Figure (4) new dataset UBPD



Feature Extraction phase

In this part of the work I used the FaceNet algorithm, in the fact that this algorithm is used for identification and in this work we only want the features of the images, so the feature extraction part was used in this algorithm, the features extracted by FaceNet were a set of 512 elements that were extracted

FaceNet trains using triplets through face-to-face matching using an online, cutting-edge triplet mining technique. This triplet, of course, comprises of a set of anchor images, each of which is made up of both positive and negative images. The FaceNet structural model is seen in Figure (5). FaceNet's deep architecture, which is deep CNN followed by L2

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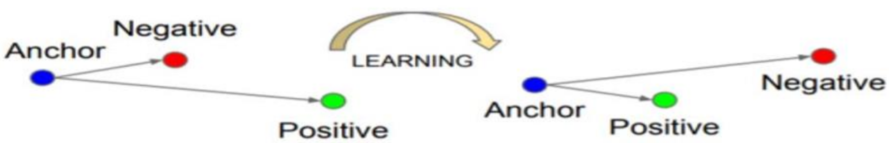
normalization, is made up of batch layers as input and produces face embedding as its output [29]. When the training process was underway, FaceNet was also pursued by the triplet loss as shown in Figure (6).

igure (5) The model structure of the FaceNet

Figure (6) The triplet loss training



Training phase

In this section Machine learning process and the process was on the as follows:

- After obtaining the Features of the images, the features are separated that do not contain pain from the features of images that contain pain.
- after the process of extracting the features by the FaceNet algorithm, which it within the trained deep learning networks, a regular fully connected ANN was used to classify the images on the basis of the features that were extracted from FaceNet, as the purpose of using such a type of network lies in the ease of installation of those networks, as it does not require high software capabilities and specifications in the computer used in the programming process, and by using this type of network, the training time was reduced by a large difference than other deep neural networks.
- In this research used Colab environment from Google to train the network that built in Python language the ANN network contains three layers as shown in Figure (7) where features (80%) were chosen for training and (20%) for the work test.

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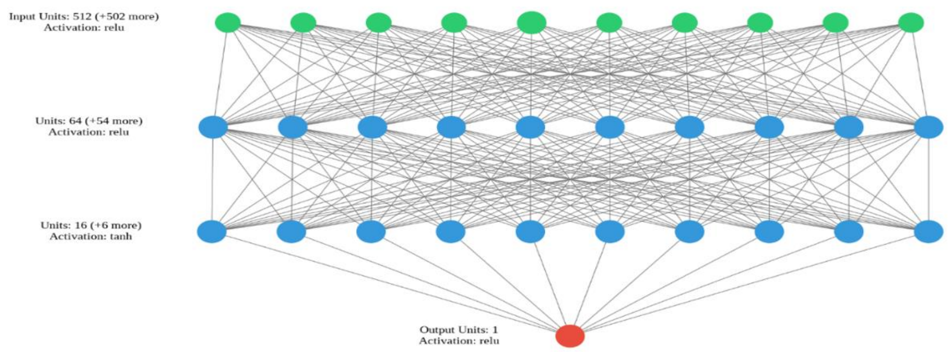
Figure (7) ANN Network



Prediction phase

Deciding if a model is performing satisfactorily as a way as conviction and legitimacy is, obviously, fundamental, and often the simplest way to do so is via empirical information.

In this part, the images that did not enter the training or even the test, which are the images left in the database, were used to determine the effectiveness of the system, and the test results on these images were very good. The validity of these results is based on our Ground Truth of dataset as shown in the result section in this paper.

4. RESULT

Unbalance Binary Pain

The binary expression of pain was selected with unbalanced data, such that all pain levels were considered to be the same, implying that the outcome was either someone with or without pain. Pictures of the training process were selected in an orderly manner so that the preparation of pictures of the same people with cases of presence and absence of pain was equal.

Table (2) Unbalance Binary Pain ANN results

Loss	Accuracy	Precision	Recall
0.0178	0.9966	0.9957	0.9931

A neural network was used and shown in Figure (7), and an accuracy level was reached (99.66%). The evaluation metrics values shown in Table (2) and the curves of the values shown in Figure (8) respectively. This led to the conclusion that the unbalanced data do not pose problems during training because we treat pain intensity estimation as a continuous regression problem. Since pain quantification is ambiguous in this model, the accuracy of the model will be very low to high levels of intensity due to the paucity of data.

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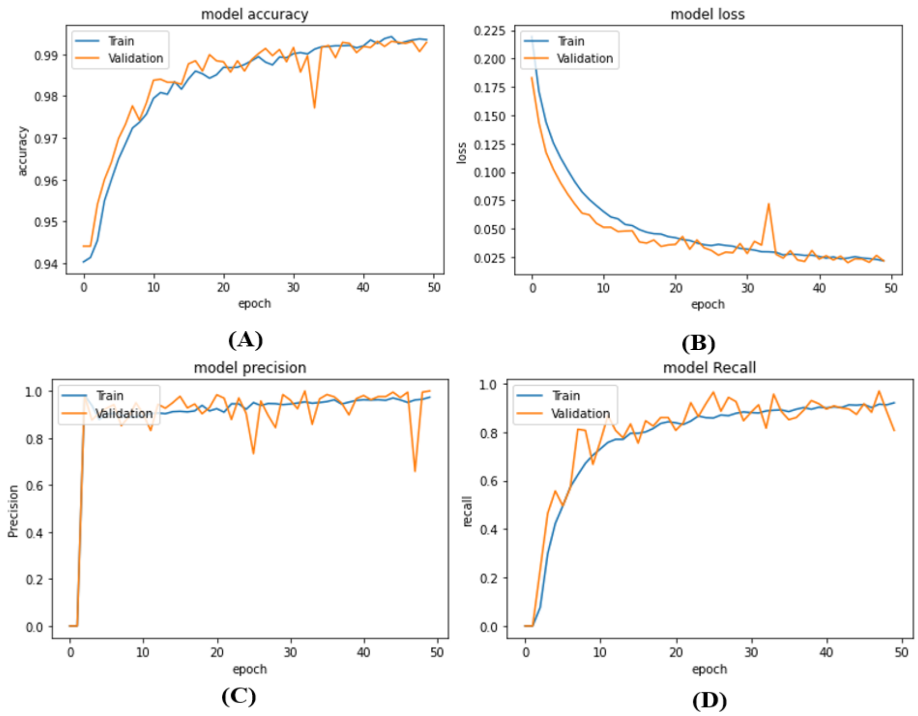
Therefore, in this work, a specific number of images of the state of no pain were selected with the rest of the images of the state of pain.

Figure (8) Unbalance Binary Pain curves



Balance Binary Pain

The feature was extracted by the FaceNet algorithm, then the feature was trained on an ANN network, (90%) were chosen for training and (10%) for testing, and the images were randomly selected for the testing process from the unhoused image in original Dataset. Our model was tested against several batch sizes and epochs as well as classification criteria using the metrics presented in Table (1). The results shown in Table (4) and it is clearly shown in Figures (9) as a curve.

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Figure (9) Balance Binary Pain curves

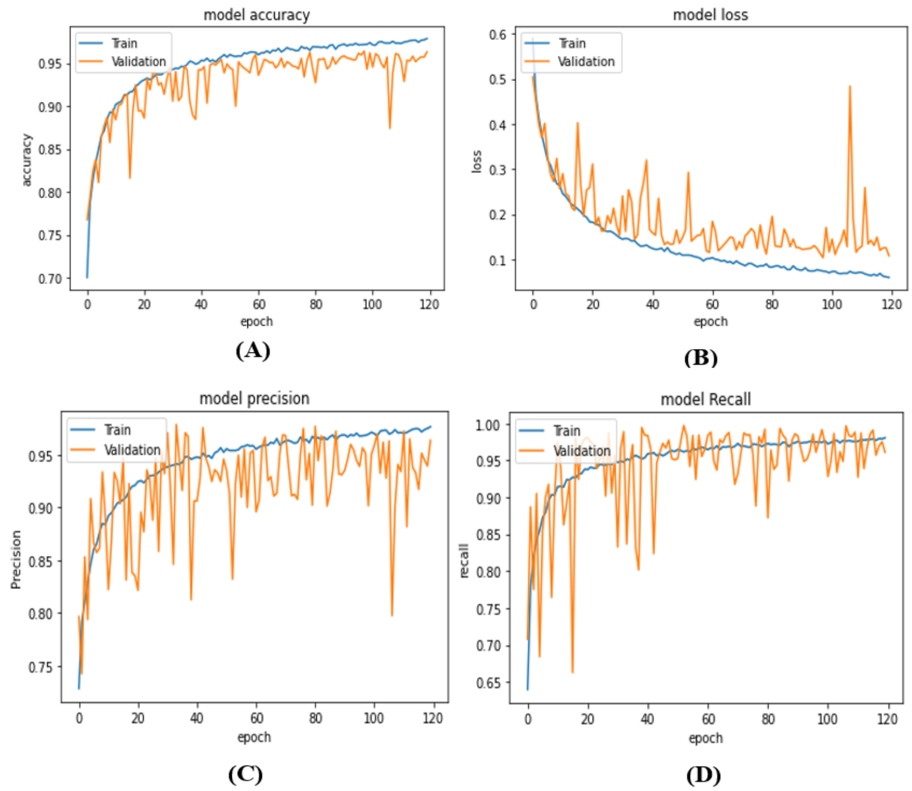

Table (4) Balanced Binary Pain ANN results

Loss	Accuracy	Precision	Sensitivity
0.1150	0.9544	0.9596	0.9514

5. DISCUSSION

To increase the real accuracy of the network, the number of images must be increased through one of the methods or one of the techniques of increasing the images, and given that the data set used contains a large number of the image but a large difference between the two states of pain and the absence of pain, the process of increasing images may reach a certain limit and become It is useless due to the lack of images of the state of pain compared to the images of the state of no pain.

Table (5) summarizes the received findings and compares them to the state-of-the art output.

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Table (5) Comparison of suggested approaches to state-of-the-art pain detection strategies

Researcher	Year	Dataset	Algorithm	Accuracy	Ref
Lucey et. al	2011	UNBC-McMaster	SVM	83.90%	[16]
Tavakolian & Hadid	2019	UNBC-McMaster	Deep Learning	98.54%	[21]
Zhou et. al.,	2020	UNBC-McMaster	RCNN	89.10%	[30]
Atee et. al	2022	-	SVM	95.00%	[26]
Present Study	2022	UNBC-Unbalance	ANN	99.66%	-
		UNBC-Balance		95.44%	

6. CONCLUSION

In binary pain, we note that the accuracy is high in the unbalanced data and less than it in the balanced data, and this is evidence that balanced data gives more accurate and logical results and the value obtained during training as a real value, but the data balanced must be taken into account that it has a significant impact on the result, and to solve this problem and increase the accuracy, modern image augmentation techniques can be used, including GAN technology, or combined with image augmentation techniques that use image wrapping, shifting and resizing or using another data set and merging it With the data within the work, but the combined data set must uses the same pain assessment criterion.

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