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TOWARDS AN AUTOMATIC PAIN INTENSITY LEVELS EVALUATION FROM MULTIMODAL PHYSIOLOGICAL SIGNAL USING MACHINE LEARNING APPROACHES

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Abstract

A pain assessment is necessary in order to identify and manage pain. Self-report has been the prime method of measuring intensity of pain. To address this, an impartial methodology to recognizing pain that is both scalable and inexpensive must be developed. In this study, a Bio-Vid Heat Pain Database (Part A) dataset containing 86 individuals in good health condition who experience extreme pain was utilized to develop algorithms for pain recognition. Two physiological indicators, electrocardiogram and electrodermal activity were utilized. Different kinds of machine learning algorithms were implemented to establish the framework for more advances in the development of complex pain classification algorithms. CatBoost and AdaBoost performed significantly better than other methods, with average performance accuracy of 83.68% and 82.68% respectively for fusion of electrocardiogram and electrodermal activity signals. The binary classification experiment discriminates between the baseline and the pain tolerance level (T0 vs. T4).

1.0 INTRODUCTION

Numerous studies suggested that it could be feasible to develop a reliable and efficient system that distinguishes between various pain levels, even if achieving so could lead to a very complicated classification (or regression) circumstance and result in poor recognition rates [1-10]. The significance of this is that, even while it is feasible to exceed the chance level by a large amount, the conclusions built in the literature and the ground actuality still vary significantly. In addition to the significant increase in demand and technological advancements in domains such as data continuity and sensor-based systems, many approaches incorporate several types of machine learning methods developed using various types of acquired physiological and video data. These methods can then be improved and utilized in both experimental and clinical situations. A variety of signals have been explored and validated in different contexts to develop pain assessment systems, depending on the number and types of sensors used during data collection. Commonly used signals include; audio (e.g. vocalizations on linguistic paralinguistic) [1-3], facial expression via video signals [4-7], physiological signals such as respiration signals (RSP), electrodermal activity (EDA), electromyography (EMG) and electrocardiogram (ECG) [8-10].

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Numerous machine learning base methods have been analyzed by the variety of data collected to successfully carry out a precise, active pain assessment task. The methods that have been suggested variety from single model approaches, which trust upon a single modality to solve the essential inference issue, to multi-modal approaches, which utilize an ensemble of numerous modalities to complete the essential pain evaluation assignment [11, 12]. Whereas, multi-modal approaches attempt to improve the robustness and performance of an implication system by relating a explicit knowledge merging method to combine a set of data from various and diverse modalities [13, 14]. The following research presents a multimodal information collection approach to the evaluation of pain level intensities based on bio physiological indicator which are established on multiple machine learning approaches [25- 27].

The BioVid database addresses the problem of subjective pain perception by using objective biological signals to classify pain intensity. This method uses physiological data, such as EEG, ECG, and skin conductance, recorded from individuals undergoing heat pain stimuli. By using these signals, the study provides a more reliable and standardized method for pain classification. The variability in pain experience also introduces noise into the data, making it difficult to develop robust models based solely on subjective pain scales. The system is trained to classify pain levels based on patterns in the BioVid signals, making it a more accurate and reliable method for pain assessment.

The work presents a multi-classifier for pain classification using simple machine learning algorithms instead of deep learning. It improves classification accuracy by including multiple physiological signals and extracting significant features from the Bio-Vid dataset. The framework also extracts significant features for pain classification, making it simpler in real-life situations and consuming less time and resources. This novel approach outperforms previous methods and offers state-of-the-art results.

The rest of this work is prepared as follows: The related research work segment provides a brief overview of a few relevant research on multimodal techniques for bio-physiological signal based pain evaluation. This includes deep learning and machine learning techniques. The proposed method section covers data that has been used to evaluate proposed machine learning approaches. The outcomes of the study are depicted in the result and discussion section finally, concludes with a discussion of the results that were obtained. Final perceptions are presented in the conclusion section.

2.0 RELATED WORK

The amalgamation of multi-modal information, combining biological signals created on the Bio-Vid Heat Pain Database (BVDB) and facial expression, became the key objective of early pain assessment research. Complicated datasets can be utilized by machine learning approaches to perform predictive modeling tasks, which have applications in the area of pain intensity research. More specifically, the limitations of subjective pain evaluation can be addressed by employing data driven algorithms. The primary purpose is to develop effective pain assessment techniques that are based on globally suitable, standardized, and objective elements. All of the approaches are referred to as automatic pain assessment [21-23].

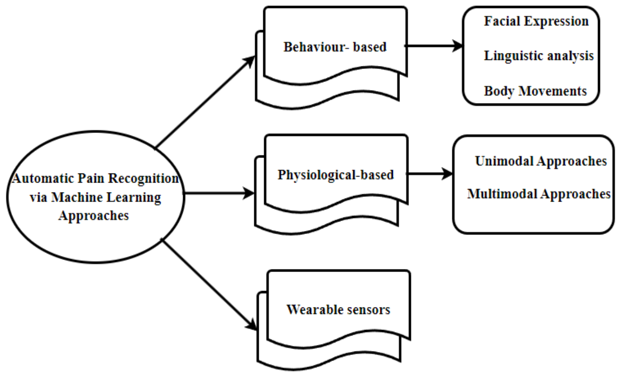

Figure 1: Schematic summary of the related work structure (Modified from Albahdal et al. [45])

Figure 1 summarizes the structure of related works. Previous studies on pain detection are initially categorized into two main groups: behavioral approaches and physiological approaches. The behavioral approaches include linguistic analysis, body language, and nonverbal cues such as bodily movements, while the physiological approaches consist of unimodal and multimodal methods. Despite this separation assists in narrative clarity, it's essential to retain in attention that assured methods use multi-modal strategies, fusing behavioral and neurophysiological methodologies. Kachele et al. [13] utilized a random forest classifier to continuously estimate the level of pain. Expressions of pain frequently cause unexpected facial expressions.

Chambers et al. [15] discovered that these phrases remain valid for all pain categories, genders, and age groups. The facial expression or action coding structure (FACS) is a systematic tool utilized to distinguish and estimate detected facial activities. Facial actions are separated into different action units (AUs) by FACS. Thiam et al. [16] developed a hybrid data consolidation method for pain evaluation on different dataset of pain, including the Bio-Vid heat pain database, based on deep de-noising CNN auto-encoders. FACS has been utilized to investigate the way individuals with various populations healthy, those with chronic pain, and those with mental syndromes express their pain [17]. The capacity to recognize the intensity of pain from facial expressions utilizing machine learning and deep learning methods has advanced significantly in recent research. Recently [18-19] designed methods for deep learning, with the latter exceeding current algorithms to evaluate pain intensity across seven levels and the former getting high accuracy in recognizing four pain intensity levels. Sri et al. [20] presented an algorithm for automatically monitoring and notifying patients that assists with ongoing evaluation and detection of pain levels through facial reaction. Werner et al. [24] utilized multi-model signals (Part-A) and a random forest method to recognize the intensity of pain. Still, analyzing the various facial regions is necessary for face expression based pain identification, which can be difficult and time-consuming in clinical environments.

Dhananjay and Sivaraman [43] constructed three machine learning algorithms to classify signals from an ECG signal dataset for sinus rhythm (SR), sinus tachycardia (ST), and atrial tachycardia (AT). In terms of sensitivity and precision, the CatBoost (CB) approach outperformed the Extra Trees (ET) and Ridge Classifier (RC) algorithms. The CB-based machine learning algorithm has the following benefits: It requires very little processing effort, produces conclusions quickly because it employs the symmetric tree technique, and reduces overfitting of the prediction owing to an integrated boosting algorithm. Khan et al. [44] developed an effective algorithm for evaluating pain intensity based on Blood Volume Pulse (BVP) data. Achieved classification accuracy of no pain vs highest pain BVP signals 79.48% using a morphological features and amalgamation of period with the support vector machine classifier. Aljebreen et al. [45] used the Bio-Vid Heat Pain dataset, containing 86 healthy individuals in acute pain, was used to develop techniques for pain recognition. Three physiological signals EGG, GSR, and EMG are combined.

3.0 METHODOLOGY

3.1 Data Set

The Bio-Vid Heat Pain Database, Part A, was used as the investigation's dataset. Philipp Werner, the head of the Bio-Vid research team, was contacted in order to obtain the data [32]. They were tested with a total of four stages of separately validated thermal pain stimulation (T1, T2, T3, and T4). There are five classes based on the pain levels, and 20 subjects in each class imply that there are 8600 samples identified for each signal. A 5.5-second time frame existed for each pain intensity. Figure 2 shows all corresponding signals available in the dataset.

3.2 Feature Extraction

The method of extracting significant characteristics from an increased data element to increase information density is called feature extraction [26]. Models that can predict the class of information gathered are constructed using these features [33-34]. In this particular case, features were determined from physiological data within the window of 5.5 seconds following the start of the painful stimuli. The time and frequency domains, which are the content from which feature domains were computed, are the main classifications for feature domains. Time domain features, following pre-processing, effectively retrieve information from the time stream sampled. In arousal quantification, where reactions to stimuli were demonstrated to be mainly time-invariant, Skin Conductance Level (SCL) time domain properties were found to be beneficial [35]. Non-stationary is demonstrated by EMG time domain analysis [36-38].

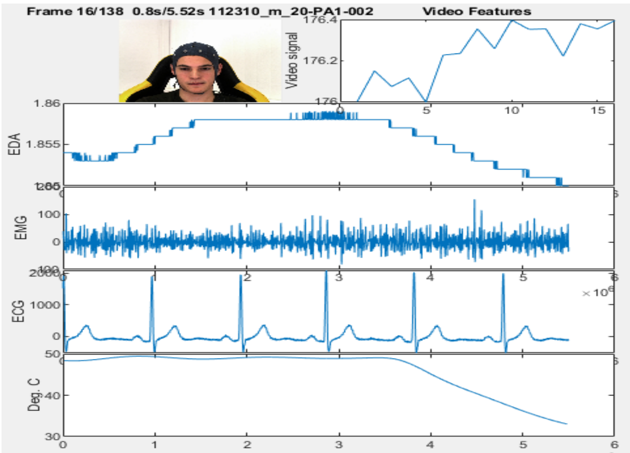

Figure 2: Recorded physiological data and video signal

3.3 Machine Learning Models

Applying a variety of classification approaches that come under the general category of supervised machine learning, we successfully managed to predict patients' pain levels based on their physiological signals [28, 29]. To anticipate pain intensity, we

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implemented four popular classification approaches: CatBoost (CB), Random Forest (RF), AdaBoost Classifier, and Support Vector Machine (SVM) [30, 31]: CatBoost and AdaBoost Classifier indicated to have better accuracy in intensity level accuracy in intensity level prediction. The four algorithms represent the majority of commonly utilized machine learning level in the healthcare sector. The proposed pain level classification method is shown in Figure 3. CatBoost, AdaBoost, Random Forest, and Support Vector Machine (SVM) are chosen for pain classification due to their strengths in handling categorical data, reducing overfitting, and handling complex physiological signals. These algorithms contribute to a robust pain classification framework.

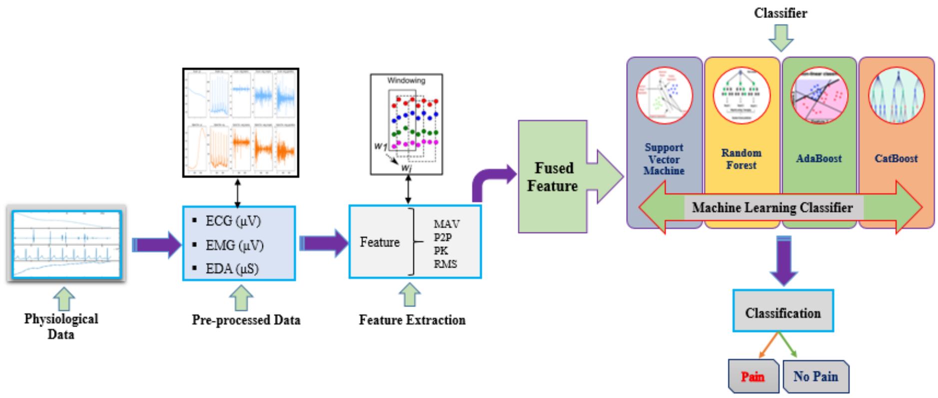

Figure 3: Proposed method for pain level classification using various classifier

3.3.1 Support vector machine

The supervised machine learning approach SVM has been widely utilized [39]. An SVM model decides an option boundary between classes based on the maximum distance to each data point after mapping data points from input space to feature space in a classification issue. Subsequently, new data points may be included in the identical feature space, providing the prediction of their groups corresponding to their placement on the decision surface. SVM would efficiently do nonlinear classification by mapping inputs into higher-dimensional feature spaces, in addition to performing linear classification like Pain, which implies the decision surface is a hyper plane.

3.3.2 Random forest

The first model for prediction that we applied was Random Forest (RF) has an overall excellent performance in many machine learning tasks [33]. Initially, random forest was introduced by [40] as are simplest and capable tool that has been utilized for machine learning in a variety of applications. The methodology built on an amalgamation of several Decision Trees (DTs) created from each trained on a different subset of the original training set of data is used in bootstrap aggregating or bagging.

The ensemble method's classification result is obtained by regression (aggregate) and can be accomplished by averaging the output of the different classifiers or by majority vote for categorization Random forests were implemented using python sklearn v1.1.3 in amalgamation with 100 DTs, with the samples essential to divide an inner node set to 2, and no output nodes is selected as the output for classification. Equation 1 was used to calculate the mean squared error, which indicates the impurity of the utilized RF repressors. Limitation on the maximum depth of the specific trees. In addition, in the binary configurations, RFs were trained for regression tasks which included two outputs, one for each class. The class that has the highest prediction among the output nodes is selected as the output for classification. Equation 1 was used to calculate the mean squared error, which indicates the impurity of the utilized RF repressors.

$$C_j = \frac{1}{N}\sum_{i=1}^{N}(y_i - \mu)^2 \qquad (1)$$

3.3.3 CatBoost

The CatBoost predictive modelling approach is a specific kind of gradient enhancement on decision trees since it is capable of handling instructed, categorical information and uses Bayesian estimation methods to prevent overfitting of the predictive model. The developed model's features are evaluated using either loss function variation or predicted parameter changes by the CatBoost automated learning method. The predicted parameter change function computes the shift in predicted values that occurs when a feature corresponding value varies. Predicted parameter changes are typically utilized to order a certain model within a group of algorithms. In this work we developed CatBoost machine learning based on predicted parameter changes model.

$$F = \{f_1, f_2, \ldots \ldots \ldots \ldots \ldots \ldots f_n\} \quad (2)$$
$$P_i = \beta_i F_i \quad (3)$$

F is a set to provide input characteristics, *P* is a prediction for that specific step, and β is the numerical factor allocated to the input features. Equation 2 indicates the collection of features that the machine learning model has been provided. *Fi* is the specific feature chosen from the provided feature set, *Pi* is the prediction value at a substituted numeric factor, and βi is the quantitative element represent in Equation 3 [41].

For pain classification, this algorithm offers novelty by handling categorical and continuous data effectively (important for multimodal data), dynamically creating features from target statistics, and ensuring a robust classification process through iterative refinement. This is particularly beneficial in the medical domain where feature diversity, interpretability, and accuracy are critical. The process involves assigning initial weights to each training example, combining features, and training a weak learner on the modified feature set. The weighted error rate is computed based on the difference between predictions and actual labels. The classifier weight is updated by increasing the weights of misclassified samples and decreasing the weights of correctly classified samples. The final output is a weighted average of predictions across all iterations, where each classifier's prediction is weighted by its accuracy. The process is repeated for a total of T iterations, with each classifier's prediction weighted by its accuracy.

3.3.4 AdaBoost

The objective of the adaptive boosting approach is to execute binary classification. The boosting concept is implemented by the AdaBoost technique to develop an effective classifier from a weak classifier. AdaBoost could boost the overall performance of machine learning classifiers by combining ineffectual classifiers and obtaining the prediction value to produce an ensemble classifier, which is a better classifier than an individual classifier. The AdaBoost algorithm reduces over fitting related issues and improves performance. It considered into account each classifier's superior values and chose the best values using a voting method. The AdaBoost approach takes into account two methods: selecting a random subset for training the complete group and training the subset with a weak classifier, along with giving the subset a weight factor [42].

4.0 RESULTS AND DISCUSSION

The study investigation indicated that the accuracies of every approach tested significantly. In the initial stages, the base level was identified from other levels (T1 to T4) using a binary classification. Table 1, Table 2, Table 3, and Table 4 show the classification accuracy of pain vs non-pain (To vs T4) for single modality and multimodality (fused single) to CatBoost, AdaBoost, Random Forest and Support Vector Machine Classifier.

Table 1: Pain classification accuracy with CatBoost classifier

Task	ECG	EMG	EDA	EDA + ECG
T0 vs. T1	48.22	48.83	60.16	62.36
T0 vs. T2	49.74	49.86	65.72	67.76
T0 vs. T3	51.26	54.38	75.79	77.29
T0 vs. T4	**66.57**	**67.89**	**81.68**	**83.68**

Table 2: Pain classification accuracy with AdaBoost classifier

Task	ECG	EMG	EDA	EDA + ECG
T0 vs. T1	48.24	47.13	60.32	56.25
T0 vs. T2	48.32	46.56	58.32	64.12
T0 vs. T3	53.58	54.23	74.57	74.66
T0 vs. T4	**67.42**	**68.59**	**81.86**	**82.68**

Table 3: Pain classification accuracy with Random Forest classifier

Task	ECG	EMG	EDA	EDA + ECG
T0 vs. T1	45.65	43.54	78.18	52.44
T0 vs. T2	48.32	46.56	58.32	60.32
T0 vs. T3	50.65	51.85	71.78	70.36
T0 vs. T4	**63.46**	**62.55**	**77.78**	**79.86**

Table 4: Pain classification accuracy with Support Vector Machine

Task	ECG	EMG	EDA	EDA + ECG
T0 vs. T1	44.32	43.22	77.18	51.38
T0 vs. T2	46.44	45.58	57.21	59.66
T0 vs. T3	52.71	50.74	70.57	69.88
T0 vs. T4	**60.25**	**61.45**	**76.76**	**79.46**

Figure 4 shows the graphical representation of the classification accuracy for each classifier. The highest level of accuracy is continuously achieved using the CatBoost and AdaBoost classifiers in all classes. The intensity level T0 (baseline) versus T4 (highest pain) classification indicated the highest accuracy, with 83.68 and 82.68, respectively. The results of the binary classification of all methods are summarized in Table 5 and also its graphical representation is shown in Figure 4. The current research's results of pain levels T0 vs T4, were compared to studies that used a binary categorization and its graphical representation shown in Figure 5. The various accuracy levels of pain intensity from the earlier research in comparison to the present research are presented in Table 6. The CatBoost classifier approach proved to be the highest performing model among all approaches. Figure 6 shows that comparison of classification accuracy with various previous methods.

Table 5: Accuracy of various machine learning method for pain vs. non pain

Classifier	ECG	EMG	EDA	EDA + ECG
SVM	60.25	61.45	76.76	79.46
RF	63.46	62.55	77.78	79.86
AdaBoost	67.42	68.59	81.86	82.68
CatBoost	**66.57**	**67.89**	**81.68**	**83.68**

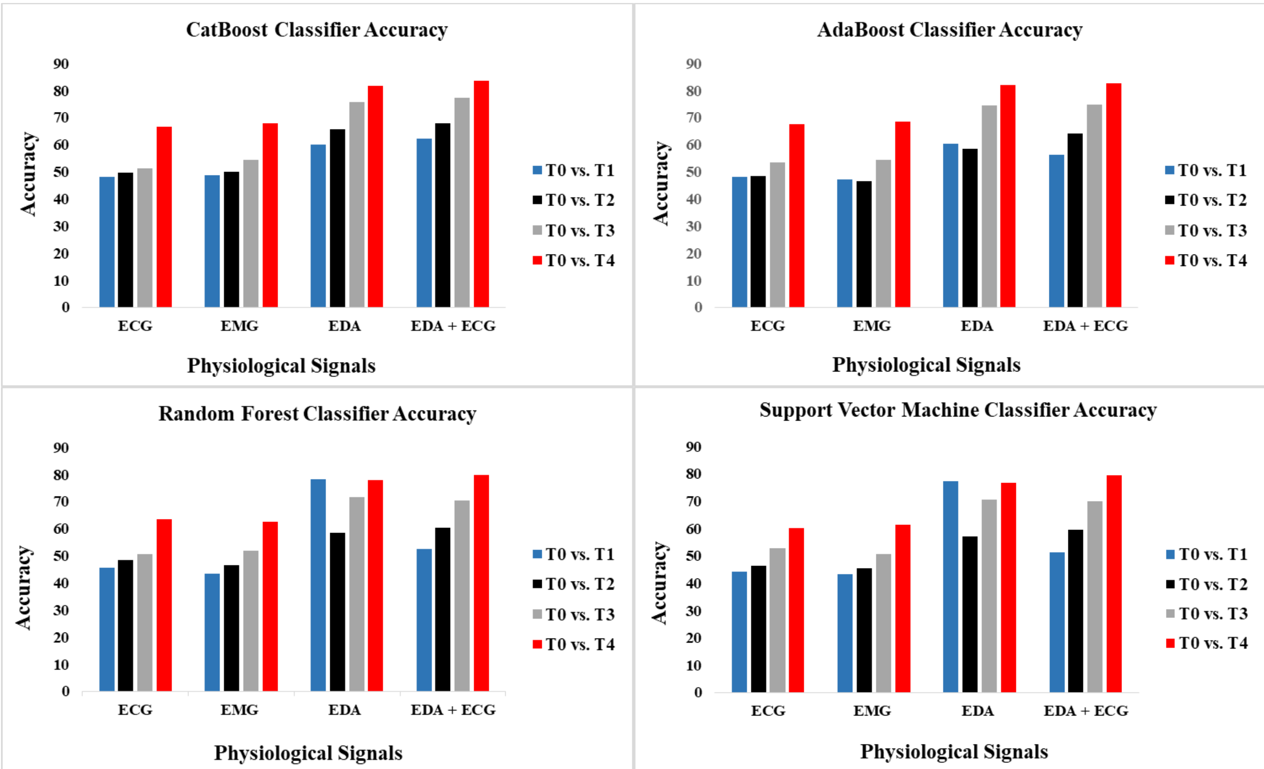

Figure 4: Graphical representation of pain level classification accuracy of each classifier

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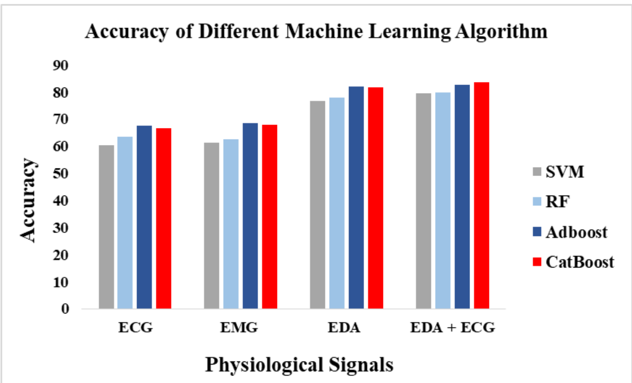

Figure 5: Comparison of pain level classification accuracy of among the various ML classifier

Overall our approach achieves identical outcomes for pain recognition by utilizing the available signals in the dataset. We conclude that the recommended approach of pain evaluation gains significant advantages from the fuse (EDA+ECG) signal. The fusion of physiological signals often per-forms well for pain categorization tasks.

Table 6: Result comparison of previous studies with accuracy metric.

Method	Classifier	Modality	Accuracy
Winslow et al. [43]	LR	ECG	79.40%
Khan et al. [44]	SVM	PPG	79.48%
Aljebreen et al. [45]	KNN	Fusion of EDA, ECG and EMG	70.10%
Aljebreen et al. [45]	NB	Fusion of EDA, ECG and EMG	72.04%
Proposed Method	**CB**	**Fusion of EDA and EMG**	**83.68%**

For pain classification, AdaBoost and CatBoost can offer superior performance compared to deep learning models when dealing with relatively small datasets or those structured with categorical features. AdaBoost, by boosting weak classifiers, enhances accuracy, while CatBoost excels in efficiently handling categorical data. Both methods can achieve high classification accuracy with reduced computational cost and complexity, making them more suitable than deep learning models for such data scenarios.

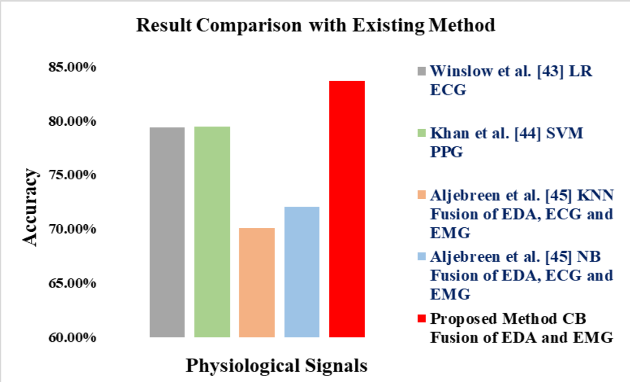

Figure 6: Result comparison of previous studies with accuracy metric

5.0 CONCLUSIONS

Various factors influence pain perception and response, making it challenging to recognize pain instantly and accurately. This research integrates physiological data from galvanic skin response, electrodermal activity, and electrocardiograms to enhance pain detection methods. Using machine learning classifiers like CatBoost and AdaBoost, feature extraction is done from these signals, with CatBoost showing superior performance in binary classification tasks. CatBoost and AdaBoost consistently achieved the highest accuracy levels across all classes, particularly in classifying intensity levels from baseline to high pain. The intensity baseline versus highest pain classification indicated the highest accuracy, with 83.68 and 82.68, respectively, for CatBoost and AdaBoost. These results show how well advanced classifiers, CatBoost and AdaBoost in particular, work together to combine multiple physiological signals to improve pain detection accuracy, especially when it comes to differentiating between baseline and high pain levels.

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