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Logistic Regression Based Model for Pain Intensity Level Detection from Biomedical Signal

Manisha Shantaram Patil*, Hitendra Dhansing Patil

Department of Computer Engineering, Shri Shivaji Vidya Prasarak Sanstha's Bapusaheb Shivajirao Deore College of Engineering, Dhule (MS), India. *Corresponding Author's Email: manishavpatil2007@gmail.com

Abstract

Hospitals today make the effort to assess acute pain with self-report assessments such as the quantitative pain the level of intensity Index and visual input index. However, because these techniques rely on patient input, they are imprecise. Thus, an objective, statistical approach to ongoing pain monitoring is necessary. In computer vision research, identifying pain intensity is a difficult challenge to solve. However, current subjective pain evaluation is unreliable because it heavily relies on the patient's response. In order to improve the standardization of pain evaluation, automated pain identification using physiological data might provide essential objective information. In the present study, we provide an objective pain recognition approach based on physiological signals that can extract novel features from electromyography (EMG), electrodermal activity (EDA), and electrocardiogram (ECG) data that have not previously been utilized for pain recognition. Utilizing the Bio-Vid Heat Pain Database (Part A) for evaluation and clinical validation, the proposed machine learning logistic regression-based method performs significantly better than previous techniques recorded in the literature for both the electrodermal activity (EDA) and fusion approaches, with average performances of 82.36% and 83.20% for the binary classification experiment that discriminates within the baseline and the pain tolerance level (T0 vs. T4). Our result shows that it outperforms most of the previously proposed methods in related works.

Keywords: Bio-potential, Classification, Feature, Logistic regression, Pain.

Introduction

The study aims to investigate pain intensity, a subjective experience, by examining its biological correlates. Pain, in its essence, is a complex sensory and emotional experience typically associated with tissue damage. It's subjective and varies greatly among individuals. Understanding the biological basis of pain intensity can provide insights into its mechanisms potential biomarkers, and therapeutic targets. Pain intensity refers to the perceived magnitude or strength of pain experienced by an individual. It can be measured on various scales, including numerical rating scales (NRS), visual analog scales (VAS), or verbal descriptor scales (VDS). This subjective experience can be influenced by factors such as psychological state, past experiences, and cultural background. Operationalizing pain intensity in terms of biological signals involves identifying physiological markers that correlate with the subjective experience of pain. This could include neurophysiological measures such as brain activity autonomic nervures system responses and biochemical markers (e.g., cytokines, neurotransmitters). By examining these biological signals alongside self-reported pain intensity measures, researchers can gain a more comprehensive understanding of the physiological processes underlying pain perception. This integration of subjective and objective measures is crucial for advancing our understanding of pain and developing more effective treatments.

The visual analog scale and numeric rating scale can be used to evaluate pain (1). These techniques, however, are only effective when the patient is cooperative and sufficiently alert that is, under circumstances that aren't often provided by the medical community (2). Additionally, there are tools available for assessing pain in individuals with linguistic as well as cognitive disorders as well as in patients receiving automatic ventilation while sedated (3). All things considered, these techniques still require improvement or verification. Conditions that prevent a sufficient meaningful assessment of pain may lead to the

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development of chronic pain, under per fusion of the operative field, or cardiac stress in individuals that are already at risk (4). Some of the research investigated the relationship between pain and a single bio-potential (5). Under conditions of tonic noxious stimuli areas of high intensity stimulation produced a higher level of skin conductance than low-intensity stimulation; the heart rate increased with short-term stimulation as opposed to prolonged stimulation, and corrugator electromyography revealed no discernible effect on the response (6-7). Our objective is to enhance pain diagnosis and pain status assessment through our research. We prepared an extensive multimodal dataset with multiple pain levels caused specifically for this purpose. A solution could be a machine learning model, such as logistic regression. The mathematical subcategories of amplitude, frequency, stationarity, entropy, linearity and variability were used to extract a total of characteristics from the electrocardiogram, skin conductance level, and face and trapezius electromyography signals. Based on logistic regression, we were given a classification rate of 83.20% for the two class problem baseline vs. pain tolerance threshold.

Related Work

The main objective of early pain assessment research was on the amalgamation of multimodal information, which included biological signals based on the Bio-Vid Heat Pain Database (BVDB) and facial expression. The BVDB collects the bio-physiological signals in the following manner:

Muscle activity is recorded by an electromyogram (EMG). The trapezius muscle is twitching, indicating an increased amount of stress, which is normal after pain stimuli (8). The electrocardiogram generated signals of the heart and provides a wealth of data regarding heart health. EDA, mentioned to as skin conductance (SC) and galvanic skin response (GSR), is a skin conductance and electrical property measurement that demonstrates a substantial correlation with the level of emotion.

Kachele et al. (8-9) utilized a random forest classifier to continuously estimate the level of pain and achieved accuracy 53.90%. Werner et al. (10) utilized multi-model signals (Part-A) and a random forest classifier to recognize the intensity of pain however with these novel ECG characteristics they were able achieve an average accuracy of 67.18%. In addition, they increased the accuracy to 81.12% by utilizing the TabNet model with ECG features.

In comparison to other signals such as the combination of EDA and ECG data signals (11) the pain categorization using EDA signals was significantly higher. These extracted characteristi cs offer more information for ECG signals that helps with pain detection (12). As an example, using a random forest classifier to compare the outcomes of the classification occupation B0 vs. P4. Gruss et al. (13) 159 features in total were retrieved, and SVM classifiers have been suggested for the binary pain classification. Significant improvements in pain recognition have been observed using deep learning and transfer learning models on physiological data. Lopez-Martinez et al. (14) two hidden layers one common and one person-specific in multi-task neural networks were given signal properties of EDA and ECG, and they outperformed single-task neural networks in terms of performance. Wang et al. (15) developed hybrid classifiers based on recurrent neural networks to categorize the level of pain. They utilized a bidirectional long short-term memory (LSTM) network for integrating manually created features with the temporal dynamic attributes of physiological inputs.

Thiam et al. (16) developed a hybrid data consolidation method for pain assessment on two separate pain databases, including the biovid heat pain database, based on deep denoising convolutional auto-encoders. Thaim et al. (17) developed a CNN (convolutional neural network) for the classification of pain based on physiological the inputs (ECG, EDA, and EMG). Pouromran et al. (18) pain intensity estimation using calculated features from ECG, EDA, and EMG data and trained the algorithms on these features such as linear regression, support vector, xgboost, and neural network. Investigators exploring pain evaluation have shifted their focus to just physiological signals due to the association identified between unpleasant pain and physiological signals. Subramaniam et al. (19) introduced an amalgamated CNNLSTM classifier for binary pain detection based on ECG and EDA inputs. Still, analysing the various facial regions is necessary for face expression based pain identification, which can be difficult and time-consuming in clinical environments. Research on pain demonstrate that

the autonomic nervous system is greatly impacted by pain, which results in variations to heart rate and EDA.

Methodology

Data Sets

A multi-modal collection of data called the Bio-Vid Heat Pain Database (Part A) (Walter et al., 2013) includes 87 healthy subjects (20) that were exposed to a total of four stages of separately standardized as well, steadily growing thermal pain stimulation (T1, T2, T3, T4). Numerous modalities, including as video signal and all bio potential signal information, were captured throughout the trials. Every single stage of pain level elicitation is arbitrarily induced 20 times, lasting 4 seconds each time. This was followed by a randomized recovery period that lasted 8 to 12 seconds. A reference point temperature T0 of 32◦C remained used throughout this recovery phase and video signal shows in Figure 1. No pain and pain signal of all physiological signal feature are shown in Figure 2.

Feature Extraction

The method of extracting significant characteristics from an increased data element in order to increase information density is called feature extraction (21). Models that can predict the class of information gathered are constructed using these features.

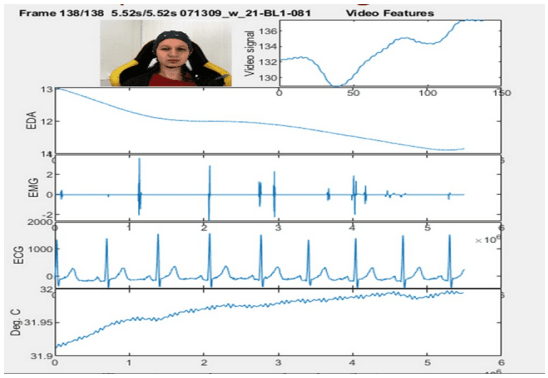

Figure 1: Recorded physiological data and video signal ECG; EMG; EDA (µS)

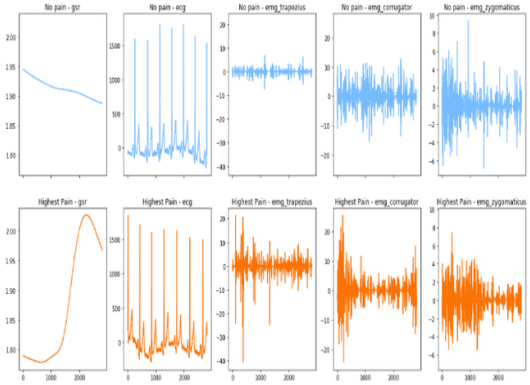

Figure 2: Top (no pain bio-potential), bottom (pain bio- potential)

The time domain and frequency domain, which are the continuums from which feature domains were computed, are the main classifications for feature domains (22). 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, SCL time domain properties were found to be beneficial (23-24). Non-stationarity is demonstrated by EMG time domain analysis (25). However, under controlled circumstances, time domain EMG characteristics have demonstrate outstanding accuracy (26). On the other hand, features in the frequency domain are determined using data that has been modified and require spectral domain characterization. It has also been demonstrated to be connected with the phasic element of SCL, the skin conductance reply. Along with these feature categories, another way to classify feature extraction methods is based on the gentle of data information they are intended to likely to theoretically. Numerous theoretical characteristics types were investigated in this study, including others that represent such as amplitude signal, frequency properties, linearity, variability, entropy, linearity, similarity, and stationarity (27). Table 1 provides a comprehensive summary of these features.

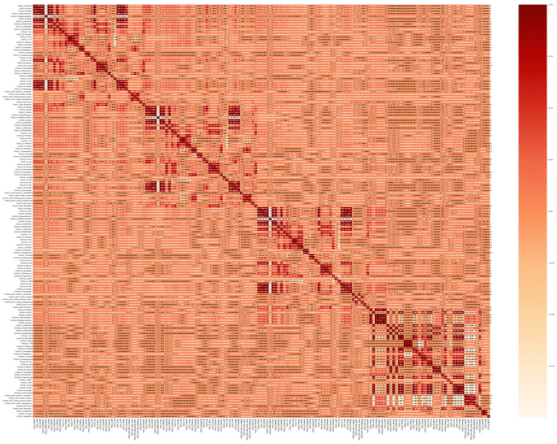

Figure 3: Pairwise variable heatmap

It shows that the ECG modality was described by 3 aspects, SCL modality by some feature. In order to determine which variable show greatest connection with the categorization and whether any particular variables provide redundant information, pairwise correlation analysis was performed shown Figure 3 and Figure 4 shows intensity distribution of few feature from listed features.

Fusion and Classification

In this research we used Biovid Pain dataset this pain database was gather data from various sources such as clinical trials, (EHRs), or self-reported assessments, ensure the data collected include relevant information such as pain intensity ratings, time stamps, and possibly contextual factors like activity levels, medication use, and physiological measurements. Employ appropriate ethical considerations and data privacy protocols, especially when dealing with sensitive health information. Identify biological signals that are correlated with pain intensity. These signals may include physiological measures such as: Electrodermal activity (EDA), Heart rate variability (HRV), Electromyography (EMG), Skin temperature, Blood pressure choose signals that are accessible, non- invasive, and feasible for continuous monitoring over time. Extract relevant features from the chosen biological signals to represent different aspects of pain intensity. Feature extraction techniques can include time-domain, frequency-domain, and time- frequency domain analyses, as well as nonlinear dynamics measures. Commonly used features may include: Statistical measures (mean, variance, skewness, kurtosis) Frequency domain measures (power spectral density) Time-domain measures (root

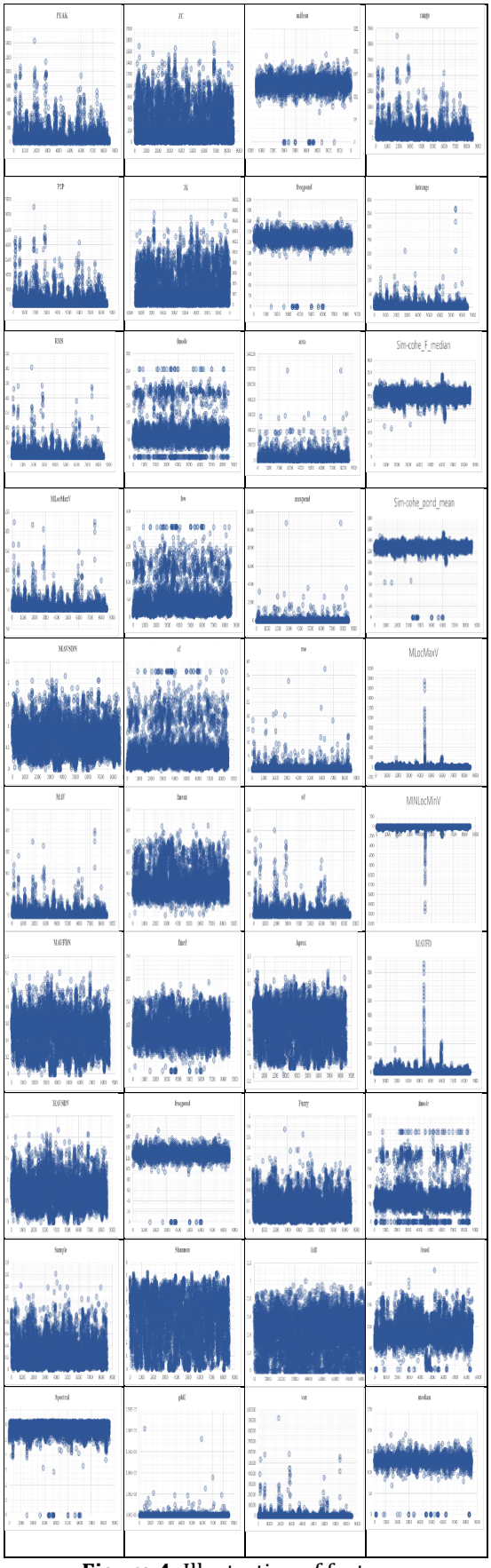

Figure 4: Illustration of features

Table 1: A Summary categories features

Feature	Group	Detail
HOMAV	Magnitude	Mean Absolute Value First Higher-Order
MAV	Magnitude	Mean Absolute Value
P2P	Magnitude	Peak to Peak Amplitude
PK	Magnitude	Peak Amplitude
RMS	Magnitude	Root Mean Square
TMNP	Magnitude	Peaks of the Mean Relative Time
TMNV	Magnitude	Mean Relative Time of the Valleys
IQR	Variability	Interquartile Range
R	Variability	Range
SD	Variability	Standard Deviation
VAR	Variability	Variance
IDS	Stationarity	Own- Interal Degree of Stationarity
MD	Stationarity	Median
ApEn	Entropy	Approximate Entropy
PLDF	Linearity	Population Lag Dependence Function
MIDS	Stationarity	Modified Integral Degree of Stationarity
FuzzyEn	Entropy	Fuzzy Entropy
SampEn	Entropy	Sample Entropy
ShannonEn	Entropy	Shannon Entropy
Spectral En	Entropy	Spectral Entropy
LDF	Linearity	Lag Dependence Function
PLDF	Linearity	Population Lag Dependence Function
MDCOH	Similarity	Median Coherence
MMNCOH	Similarity	Modified Mean Coherence
BW	Frequency	Bandwidth
CF	Frequency	Center Frequency
MDF	Frequency	Median Frequency
MNF	Frequency	Mean Frequency
MOF	Frequency	Mode Frequency
ZC	Frequency	Zero Crossings
MNRR	Variability	Mean Resting Rate
RMSSD	Variability	Root Mean Square Consecutive Interval Variations
SDMN	Stationarity	Standard Deviation of Mean Vector
LDF	Linearity	Lag Dependence Function
SDSD	Stationarity	Standard Deviation of Standard Deviation Vector

mean square, entropy) Wavelet transforms Consider domain knowledge and previous research to guide the selection of features that are likely to capture meaningful information related to pain intensity. Split the data into training, validation, and test sets to evaluate model performance and prevent overfitting. Train the model using the training set and optimize model parameters using techniques such as cross-validation, grid search, or Bayesian optimization. Evaluate the model's performance on the validation set using appropriate metrics. Fine-tune the model as needed based on validation results and retrain it on the entire training set.

Fusion of data and stimulus classification follow next after feature extraction. An early fusion model is utilized in this work. All feature vectors from the various modalities are merged. Higher-dimensional feature vectors that are standardized for each individual are produced by converting each variable into a z-score dependent on the corresponding individual-specific average and standard deviation. Proposed pain level classification method shown in Figure 5. Initially pre-processes physiological signal, after that relevant feature extracted shown in Table 1 and for classification in this work we use logistic regression (LA) machine learning classifier to classify level of pain intensity.

Logistic Regression

Logistic regression is a supervised machine learning algorithm that accomplishes binary classification tasks by predicting the probability of an outcome, event, or observation. The model delivers a binary or dichotomous outcome limited to two possible outcomes: yes/no, 0/1, or true/false. A machine learning model can be effectively set up with the help of training and testing. The training identifies patterns in the input data and associates them with some form of output. Training a logistic model with a regression algorithm does not demand higher computational power. As such, logistic regression is easier to implement, interpret, and train than other ML methods. Logistic regression uses a logistic function called a sigmoid function to map predictions and their probabilities. The sigmoid function refers to an S-shaped graph.

Moreover, if the output of the sigmoid function is greater than a predefined threshold on the graph, the model predicts that the instance belongs to that class. If the estimated probability is less than the predefined threshold, the model predicts that the instance does not belong to the class. The sigmoid function shown in equation 1 is referred to as an activation function for logistic regression and is defined as:

$$f(\chi) = \frac{1}{1 + e^{-\chi}} \quad [1]$$

The equation 2 represents logistic regression:

$$y = \frac{e^{(b_0 + b_1 X)}}{1 + e^{(b_0 + b_1 X)}} \quad [2]$$

The only machine learning approach that is not a black box model is logistic regression. Black box models are typically complex but logistic regression illustrates exactly the framework executes in reality. A typical, multinomial, or binary logistic regression can be utilized. It is a binary logistic regression in this instance. The logistic regression model's equations that are shown in equation 3 and 4.

$$P(y|x) = rr(x) \quad [3]$$

$$\pi(x) = \frac{\exp(\beta_0 + \beta_1 x_{1i} + \cdots + \beta_p x_{pi})}{1 + \exp(\beta_0 + \beta_1 x_{1i} + \cdots + \beta_p x_{pi})} \quad [4]$$

Probability computations are performed for predicting classes in the Logistic Regression technique. Applying the threshold value as an estimate is necessary for classification data created on the binary reply data. A cut point of 0.5 could be applied. Class 0 is the predicted result if the possibility generated by the algorithm is below 0.5, and Class 1 is the predicted outcome if the possibility generated by the algorithm is greater than or equal to 0.5 (28). The stages for

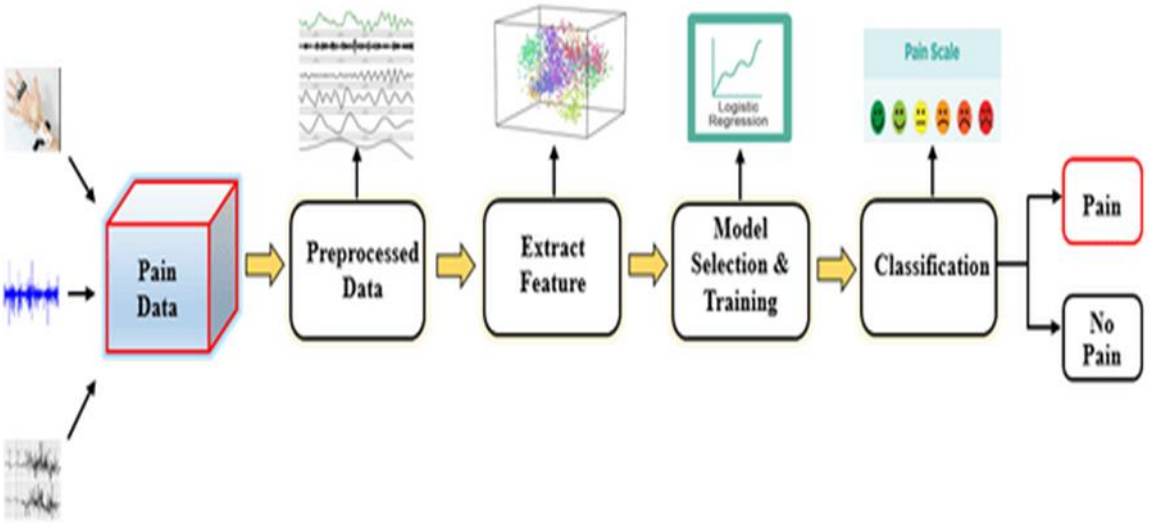

Figure 5: Pain classification framework

categorizing the logistic regression approach are listed below:

- Determine which factor is dependent, then split it into binary data scores of 0 and 1, which represent respectively.
- Fail or successful situations.
- Calculate the intercept (a) and coefficient value (β) associated with each variable that is independent express in equation 5.

$$a = \bar{\bar{y}} - \beta\bar{x} \qquad [5]$$

- In order to generate a linear model from a logistic model, transformations is required because the logistic model is non-linear. Generate a probabilistic framework using the logistic function that equation 2 produced.
- Data obtained from the logistic and probability models are entered into the regression model, which is then tested.

It belongs to category 0 if the value of π(x) is less than 0.5 and category 1 if n(x) equal 0.5.

Logistic regression is a commonly used statistical method for binary classification tasks, where the goal is to predict the probability that an instance belongs to one of two classes. In the context of pain classification, logistic regression can be a valuable tool for determining the likelihood that a certain set of features or variables is associated with the presence or absence of pain. Validity in the context of logistic regression refers to the extent to which the model accurately reflects the underlying relationship between the predictors (features) and the outcome variable (presence or absence of pain).This involves ensuring that the variables included in the model are relevant and that the assumptions of logistic regression are met Validity can be enhanced by carefully selecting variables based on theoretical understanding and empirical evidence, as well as by assessing model fit and performance through techniques like cross-validation. Reliability in logistic regression pertains to the consistency and stability of the model's predictions over repeated samples or observations. A reliable logistic regression model should produce consistent results when applied to different datasets with similar characteristics. This can valuated through measures such as confidence intervals, which provide an indication of the precision of the estimated coefficients, and by conducting sensitivity analyses to assess the robustness of the findings to variations in the data or modelling assumptions.

In the context of pain classification, the validity of a logistic regression model representativeness of the sample features such as pain intensity, location, duration, and associated symptoms would contribute to the validity of the model. Reliability in pain classification using logistic regression would involve demonstrating that the model produces consistent predictions across different patient populations or settings.

This could be assessed by applying the model to independent datasets or by conducting validation studies in diverse clinical settings. Overall, while logistic regression can be a useful methodology for pain classification, ensuring both validity and reliability requires careful attention to model development, validation, and interpretation. Additionally, it's important to acknowledge the limitations of logistic regression, such as its assumption of linearity between the log odds of the outcome and the predictor variables, and to consider alternative modelling approaches when appropriate.

The dataset is randomly split into 80% training and 20% testing sets in the train/test splitting with k = 7, which results with slightly higher accuracy and area under the curve but lower compute complexity than k = 10 across the majority of ML models. This is done after the data has been pre-processed. As a result, 7-fold cross validation has been used to assess the precision of machine learning models.

Logistic regression is susceptible to overfitting, especially when the number of features is large relative to the number of observations. Regularization techniques such as L1 (Lasso) regularization can help prevent overfitting by penalizing large coefficients.

Results and Discussion

Assess the model's performance using a combination of evaluation metrics such as MAE, MSE, RMSE, MAPE, R-squared, and correlation coefficient. Compare the model's performance against baseline models or alternative forecasting methods to gauge its effectiveness. Conduct sensitivity analysis to evaluate the robustness of the model to changes in input parameters or assumptions. Use techniques such as feature importance or coefficient analysis to determine the relative importance of predictors in the model. Identify which biological signals or features contribute most significantly to the prediction of pain intensity. Consider the clinical relevance of predictors and prioritize those that align with physiological mechanisms or known risk factors for pain**.**

For regression models, interpret the coefficients to understand the direction and magnitude of the effect of each predictor on the pain intensity. positive coefficients indicate that an increase in the predictor variable leads to an increase in pain intensity, while negative coefficients suggest the opposite. Consider the scale and units of the predictor variables when type of model used (linear, nonlinear, time series) and the feature engineering techniques applied. Translate model findings into clinically meaningful insights by considering how changes in predictor variables may impact collaborate with healthcare professionals to validate model findings and assess their clinical relevance and applicability. Incorporate patient-reported outcomes and subjective assessments to complement objective predictors and provide a holistic understanding of pain intensity dynamics. There are various metrics are used to determine the performance of classifier (model) such as sensitivity, specificity, and accuracy. After the classification algorithm has produced predictions, we were to want to determine the accuracy of those predictions. Since the metrics that are important to your model may change based on its intended application, accuracy in classification models can be an especially complex notion. We have fit a logistic regression model on dataset to try and predict. We have some predictions, we can evaluate the model to determine how well it is predicting the actual class. A key piece in understanding the accuracy of our model is the confusion matrix.

We evaluate the proposed approach on the Bio-Vid Heat Pain Database's Part A as the basis. The LOSO cross validation approach is employed, whereas a subject gets assigned as a test, and the other subjects are utilized for train the model. In order to evaluate the training process average accuracy (in percentage terms) with previous studies is provided. We take approximately four binary classification tasks to recognize pain. In this investigations additionally we utilize of other modalities.

The results of the categorization tasks for subjects 87 are displayed in Table 2. We conclude that the recommend approach for pain evaluation gain significant advantages from EDA signal. The fusion of physiological signal. The fusion of physiological signal often performs well for pain categorization tasks. The Table 3 presents the evaluation of the suggested method according to the maximum pain classification compared to previous studies. In Table 2, we evaluate fused signal and EDA, and for 87 participants, we achieve an accuracy of 83.20%

and 82.36%, respectively. We achieved the best performance for fused signals for the classification of Pain level 0 vs Pain level 4. Table 3 shows the way the proposed method performs on classification tasks in comparison to numerous of earlier method, for different classification methods, for different classification tasks, the suggested approach performs more effectively than other approaches in most cases. Figure 6 shows that classification accuracy of different modality and Figure 7 show that comparison of classification accuracy with various previous method.

Table 2: Binary classification accuracy with multiple signals and fusion signal

Task	ECG	EMG	EDA	Fusion
T0 vs T1	49.17	49.15	61.76	61.12
T0 vs T2	50.21	50.92	66.93	66.86
T0 vs T3	52.80	53.52	76.38	76.19
T0 vs T4	**57.40**	**58.59**	**82.36**	**83.20**

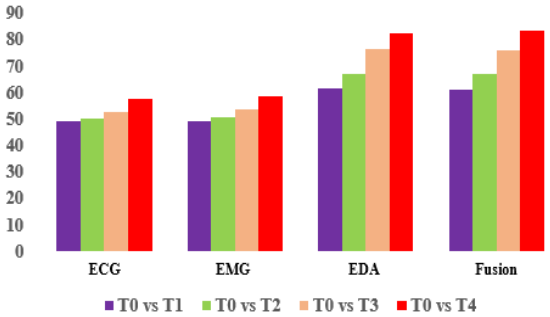

Figure 6: Bio-potential signals accuracy

Table 3: An assessment of the binary classification accuracy among T0 and T4 using all bio-signals is carried out

Method	Modality	Accuracy
Kachele et al. [9]	Multimodal signals	82.00
Werner et al. [2]	Multimodal signals	76.60
Lopez-Martinez et al. [14]	Multimodal + videos	80.60
Proposed LR Method	Multimodal signals	83.20

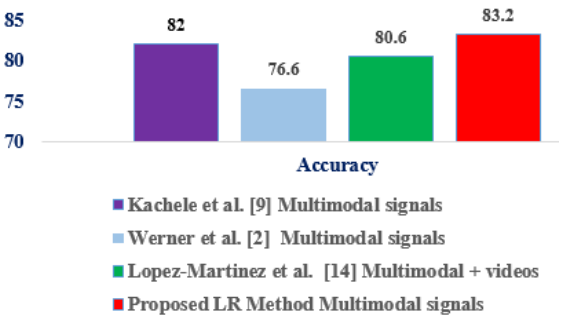

Figure 7: Comparison of classification accuracy between T0 and T4

Logistic regression methodology in pain intensity classification involves rigorous selection of predictor variables, validation against external criteria, transparent reporting of results, and assessment of time points. Valid and reliable logistic regression models can provide valuable insights into the factors influencing pain intensity and aid in clinical decision- making and treatment planning.

The adoption of ML in pain treatment and research offers transformative opportunities to enhance patient care, optimize treatment outcomes, and advance our understanding of pain disorders. However, it also requires careful consideration of ethical, regulatory, and practical considerations to realize its full potential in clinical practice.

Conclusion

Overall our approach achieves identical outcomes for pain recognition by utilizing the available signals in the dataset.

Further research in these fields may substantially modify the development of new treatments and enhance current knowledge of and treatment of individuals suffering pain by utilization of advanced data fusion techniques, such as deep learning architectures and Bayesian networks, to extract meaningful insights from multimodal datasets and uncover hidden relationships between variables.

Abbreviation

EMG: Electromyography
EDA: Electrodermal Activity
ECG: Electrocardiogram
SC: Skin Conductance
GSR: Galvanic Skin Response
ECG: Electrocardiogram
LA: Logistic Regression

ML: Machine Learning
HOMAV: Mean Absolute Value First Higher-Order
RMS: Root Mean Square
IQR: Interquartile Range
LOSO: Leave One Subject Out

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Author Contributions

The whole article has been written, reviewed, implemented, developed, and analyzed by all authors.

Conflict of Interest

The authors declare no conflict of interest.

Ethics Approval

The research study used dataset in compliance with Helsinki's ethical norms (ethics committee: 196/10-UBB/bal.).

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