# Multimodal Pain Recognition in Postoperative Patients: A Machine Learning Approach

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## *Abstract*

**Background:** Acute pain management is critical in postoperative care, especially in vulnerable patient populations that may be unable to self-report pain levels effectively. Current methods of pain assessment often rely on subjective patient reports or behavioral pain observation tools, which can lead to inconsistencies in pain management. Multimodal pain assessment, integrating physiological and behavioral data, presents an opportunity to create more objective and accurate pain measurement systems. However, most prior work has focused on healthy subjects in controlled environments, with limited attention to real-world postoperative pain scenarios. This gap necessitates the development of robust, multimodal approaches capable of addressing the unique challenges associated with assessing pain in clinical settings, where factors like motion artifacts, imbalanced label distribution, and sparse data further complicate pain monitoring.

**Objective:** To develop and evaluate a multimodal machine learning-based framework for the objective assessment of pain in postoperative patients using biosignals such as electrocardiogram (ECG), electromyogram (EMG), electrodermal activity (EDA), and Respiration Rate signals.

**Methods:** The iHurt study was conducted on 25 postoperative patients at the University of California, Irvine Medical Center. The study captured multimodal biosignals during light physical activities, with concurrent self-reported pain levels using the Numerical Rating Scale (NRS). Data preprocessing involved noise filtering, feature extraction, and combining handcrafted (HC) and automatic features through convolutional and long-short-term memory autoencoders. Machine learning classifiers, including Support Vector Machine (SVM), Random Forest (RF), AdaBoost, and K-Nearest Neighbors (KNN), were trained using weak supervision and minority oversampling to handle sparse and imbalanced pain labels. Pain levels were categorized into baseline (BL) and three levels of pain intensity (PL1-3).

**Results:** The multimodal pain recognition models achieved an average balanced accuracy of over 80% across the different pain levels. Respiratory rate (RR) models consistently outperformed other single modalities, particularly for lower pain intensities, while facial muscle activity (EMG) was most effective for distinguishing higher pain intensities. Although single-modality models, especially RR, generally provided higher performance compared to multimodal approaches, our multimodal framework still delivered results that surpass previous works in terms of overall accuracy. This suggests that while RR remains a strong modality on its own, the combination of multiple biosignals offers valuable insights and potential improvements for more complex pain recognition tasks in clinical settings.

**Conclusions:** This study presents a novel, multimodal machine learning framework for objective pain recognition in postoperative patients. The results highlight the potential of integrating multiple biosignal modalities for more accurate pain assessment, with particular value in real-world clinical settings. Future work should focus on developing personalized models to account for individual variability in pain responses, ultimately improving clinical pain management

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**Keywords:** Pain intensity recognition, multimodal information fusion, signal processing, weak supervision, healthcare

## Introduction

Pain is defined by the International Association for the Study of Pain (IASP) as “an unpleasant sensory and emotional experience associated with actual or potential tissue damage or described in terms of such damage” [1]. Pain is a unique phenomenon that individuals experience and perceive independently. Younger et al. [2] stated that pain is a subjective experience for which there is no current objective measure. Pain may be classified as either acute or chronic; Kent et al. [3] described acute pain as encompassing the immediate, time-limited bodily response to a noxious stimulus that triggers actions to avoid or mitigate ongoing injury. Chronic pain was first defined loosely by Bonica [4] as pain that extends beyond an expected timeframe; currently, chronic pain is defined as “persistent or recurrent pain lasting longer than three months” [5]. The focus of this paper is on acute pain.

Acute pain is a common experience in the post-anesthesia care unit (PACU) in the immediate period following surgery. According to Chou et al. [6], pain occurs in 80% of patients following surgery, and 75% of patients with pain report their pain as either moderate, severe, or extreme. Current guidelines for the assessment of pain in the PACU recommend using a Numerical Rating Scale (NRS) or Verbal Rating Scale (VRS) for patients who are sufficiently awake and coherent to reliably report pain scores [7]. However, Herr et al. [8] identified several patient populations who are at risk for being incapable of providing self-report scores of pain; specifically, these populations include the pediatric population who have yet to develop adequate cognition, elderly patients with dementia, individuals with intellectual disabilities, and those who are unconscious, critically ill, or terminally ill. In these patient populations, Small et al. [7] recommend the use of behavioral pain scales, such as the Pain Assessment in Advanced Dementia (PAINAD), Critical Care Pain Observation Tool (CPOT), or Behavioral Pain Scale (BPS). Despite the pain assessment measures of self-report and behavioral pain scales, each of these methods may be prone to biases. For example, Craig et al. [9] discussed how self-report may be a means to obtain a particular goal that can be influenced by the individual reporting pain. Additionally, Hadjistavropoulos et al. [10] provided the Communications Model of Pain which provided a basis for how expressive behaviors are decoded by observers of individuals in pain, which are influenced by the message clarity transmitted by the individual in pain as well as the unique biases (e.g., knowledge level, assessment skills, and predisposing beliefs) of the individual assessing pain. The difficult nature of interpreting pain scores has resulted in disparities in pain management in minority populations, with research by Staton et al. [11] showing that the black race is a significant predictor of the underestimation of pain by physicians.

Multimodal pain assessment represents one potential method of circumventing the limitations of traditional self-report and behavioral pain assessment tools and an opportunity for enhancing pain assessment in vulnerable populations. Instead of having to rely on only one dimension of pain assessment, such as behaviors through the use of the CPOT or BPS scales, future multimodal pain assessment will incorporate physiological indicators, such as electrodermal activity (EDA), electrocardiogram (ECG), electroencephalogram (EEG) and electromyogram (EMG) as well as behaviors (e.g. facial expression), and perhaps other as-yet undiscovered parameters to capture pain assessment in patient populations that might not be best represented by current assessment strategies. For example, a study by Gélinas et al. [12] found that revisions to the CPOT were necessary because some brain-injured patients may not exhibit certain behaviors that are contained in the CPOT. Similarly, for individuals diagnosed with dementia, Achterberg et al. [13] stated that there is a preponderance of observer-based pain assessment tools, however, these tools retain significant differences between them, as well as concerns for lack of reliability, validity, and sensitivity of change. Enhancing pain assessment through the combination of traditional pain assessment methods with novel multimodal approaches may serve to eventually enhance pain assessment in a greater

majority of vulnerable patient populations.

With the advent of connected Internet-of-Things (IoT) devices and wearable sensor technology, automated data collection may achieve continuous pain intensity measurement. A significant amount of research has been conducted in recent years which has sought to develop methods of continuous, automatic, and multimodal pain assessment. For example, prior work conducted by Walter et al. [14] and Werner et al. [15] used skin conductance level (SCL), ECG, electroencephalogram (EEG), and EMG to monitor pain in response to thermal pain. Other works, such as Hammal et al. [16] and Werner et al. [17] have incorporated facial expression monitoring as an indicator of pain. While these studies were immensely beneficial to the scientific community in terms of their contributions to a better understanding of techniques to obtain continuous pain assessment, the setting of these experiments was in highly controlled laboratory environments from healthy participants. Collecting data in real-world situations as opposed to a laboratory setting would allow the researchers to assess a pain assessment technique's potential in relation to actual pain brought about through a surgical procedure instead of induced pain.

To the best of our knowledge, this is the first work proposing a multimodal pain assessment framework for post-operative patients. It should be noted that a pain assessment study on real patients is associated with several challenges (e.g., imbalanced label distribution, missing data, motion artifacts, etc.) since several parameters such as the intensity, distribution, frequency, and time of the pain as well as the environment cannot be controlled by researchers. Our main contributions are four-fold:

- We conducted a clinical study for multimodal signal acquisition from an acute pain unit of the University of California, Irvine Medical Center (UCIMC)
- We propose a multimodal pain assessment framework using our database (iHurt Pain DB) collected from postoperative patients while obtaining a higher accuracy compared to existing works on healthy subjects [17].
- We use both handcrafted (HC) and automatically generated features outputted from deep learning networks to build our models.
- We provide a novel method to mitigate the presence of sparse and imbalanced labels (due to the real clinical setting of the study) using weak supervision and minority oversampling.

The subsequent sections are organized as follows. Section three talks about related research on this topic. Section four gives a brief overview of our study design. Sections five, six, and seven explain our multimodal framework, the experiments we performed, and the discussion of their results. Finally, Section Eight concludes the paper and outlines future research directions.

## Methods

The study was approved by the University of California, Irvine, institutional review board (IRB) (HS: 2017-3747). Candidates were selected from the Acute Pain Service (APS) patient list at UC Irvine Health in Orange, CA, USA. The APS unit at the medical center serves approximately 100 patients weekly enabling the lead Doctor of Medicine (M.D.) to recruit patients. This is the first claimed study that collected biosignals from postoperative adult patients in hospitals. All participants (age: 23 - 89 years) were recruited to the study from July 2018 to October 2019.

### *iHurt Study Design*

We conducted a biomedical data collection study on 25 post-operative patients reporting various degrees of pain symptoms. Multimodal biosignals (ECG, EMG, EDA, PPG) were collected from patients likely having mild to moderate pain, who were asked to perform a few light physical activities while acquiring data. We also collected primary demographic information from each patient including height, weight, sex, and body mass index. All signals were collected using the iHurt system.

## *iHurt System*

iHurt is a system that measures facial muscle activity (i.e., changes in facial expression) in conjunction with physiological signals such as heart rate, heart rate variability, respiratory rate, and electrodermal activity for the purpose of developing an algorithm for pain assessment in hospitalized patients. The system uses the two following components to capture raw signals:

**1) Eight-Channel Biopotential Acquisition Device:**
Our team at the University of Turku, Finland developed a biopotential acquisition device to measure ECG and EMG signals. The device incorporates commercially available electrodes, electrode-to-device lead wires, an ADS1299-based portable device, and computer software (LabVIEW version 14.02f, National Instruments) to visualize data streaming from the portable device. Raw signals from the electrodes are sampled at 500 samples per second and are sent to the computer software via Bluetooth for visualization [35].

**2) Empatica E4:**
We use the commercially available Empatica E4 wristband (Empatica Inc, Boston, MA, USA) [33] to measure EDA and PPG signals. The purpose of using a wristband was to allow our participants to move freely without any impediments. The Empatica E4 was connected to the participants' phones over Bluetooth for visualization.

We removed 3 participants' data from the final dataset due to the presence of excessive motion artifacts. We also excluded 2 additional patients since they were wearing the Empatica E4 watch on their arm that received IV (intravenous) medication. This resulted in unreliable EDA signals due to conditions like skin rash and itching. This left us with data from 20 patients to build our pain recognition system. The dataset also contains rich annotation with self-reported pain scores based on the 11-point Numeric Rating Scale (NRS) from 0 – 10. A detailed explanation of the dataset and the study design can be found in [37]. We intend to make the de-identified dataset available to the research community for further analysis and applications.

## *Data Processing Pipeline*

The first step in building our multimodal pain assessment system was to process the raw signals collected during trials. The data processing pipeline consisted of the following steps:

- We filtered the signal to remove powerline interference, baseline wander, and motion artifact noise.
- We performed feature extraction on the filtered signals to obtain amplitude and variability features in the time domain. The time domain features were extracted using 5.5-second and 10-second windows. The 5.5-second window size was extracted to compare with prior work [17].

- In addition to HC features, we also used automatic features which were outputted from a deep neural network.
- Once the features were extracted, we tagged them with their corresponding labels based on the nearest timestamp of the label.
- Each of these processing steps was applied individually to each of the four modalities. Processed data from each of the modalities were combined using either early fusion (EF) or late fusion (LF). The types of HC features extracted from each modality and the deep learning pipeline for extracting automatic features are described in detail.

## *ECG Handcrafted Features*

The ECG channel was filtered using a Butterworth band-pass filter with the frequency ranges of [0.1,250] Hz. The HRV HC features were extracted with pyHRV, an open-source Python toolbox [38] using the R-peaks extracted from the ECG signal via a bidirectional long short-term memory network [39]. These features were extracted from two window sizes, 5.5 and 10 seconds. There were 19 time-domain (TD) features. The TD features extracted from NN intervals, or the time interval between successive R-peaks, comprised of the slope of these intervals, 5 statistical features (total count, mean, minimum, maximum, and standard deviation), 9 difference features (mean difference, minimum difference, maximum difference, standard deviation of successive interval differences, root mean square of successive interval differences, number of interval differences greater than 20ms and 50ms, and percentage of successive interval differences that differ by more than 20ms and 50ms), and 4 heart rate features (mean, minimum, maximum, and standard deviation).

## *EMG Handcrafted Features*

The preprocessing phase of EMG channels comprised of a 20Hz high pass filter and two notch filters at 50Hz and 100Hz all using a Butterworth filter. Like ECG features, we extracted EMG features from 5.5 and 10-second windows on 5 different channels for each major facial muscle. The 10 amplitude features extracted were 1) peak, 2) peak-to-peak mean value (p2pmv), 3) root mean squared (rms), 4) mean of the absolute values of the second differences (mavsd), 5) mean of the absolute values of the first differences (mavfd), 6) mean of the absolute values of the second differences of the normalized signal (mavsdn), 7) mean of the absolute values of the first differences of the normalized signal (mavfdn), 8) mean of local minima values (mlocminv), 9) mean of local maxima values (mlocmaxv), and 10) mean of absolute values (mav). The 4 variability features were 1) variance, 2) standard deviation, 3) range, and 4) interquartile range. All 14 features were calculated for 5 different EMG channels resulting in 70 EMG features in total.

## *EDA Handcrafted Features*

We used the pyEDA library [40] for pre-processing and feature extraction of EDA signals. In the pre-processing part, first, we used a moving average across a 1-second window to remove the motion artifacts and smooth the data. Second, a low-pass Butterworth filter on the phasic data was applied to remove the line noise. Lastly, preprocessed EDA signals corresponding to each different pain level were visualized to ensure the validity of the signals. In the feature extraction part, the cvxEDA algorithm [41] was employed to extract the phasic component of EDA signals. The EDA signals' peaks or bursts are considered variations in the phasic component of the signal. Therefore, the clean signals and extracted phasic component of signals were fed to the statistical feature extraction module to extract the number of peaks, the average value, and the maximum and minimum value of the signals. Moreover, these extracted features were further employed in the post-feature extraction

module to extract 8 more features: (1) the difference between the maximum and the minimum value of the signal, (2) the standard deviation, (3) the difference between the upper and lower quartiles (4) root mean square, (5) the mean value of local minima, (6) the mean value of local maxima, (7) the mean of the absolute values of the first differences, and (8) the mean of the absolute values of the second differences. This resulted in 12 EDA features in total.

PPG-based Respiratory Rate Handcrafted Features

We pre-processed the PPG signal before extracting the respiratory rate from it. Two filters were used during the preprocessing. We first used a Butterworth bandpass filter to remove noises including motion artifacts. Then, a moving average filter was implemented to smooth the PPG signal. After that, we applied an Empirical Mode Decomposition (EMD) based method proposed by Madhav et al. [42] to derive respiration signals from filtered PPG signals. This method was proven to derive RR from a PPG signal with high accuracy (99.87%). Ten features were extracted from the respiratory signal including (1) the number of inhale peaks, (2) the mean value of the signal, (3) the maximum value (4) the minimum value (5) the difference between the maximum and the minimum value, (6) standard deviation, (7) the average value of the inhale peak intervals, (8) the standard deviation of the inhale peak intervals, (9) the root mean square of successive differences between adjacent inhale peak intervals, (10) standard deviation of inhale duration/average inhale duration. A visualization of the HC feature pipeline is shown in Figure 1.

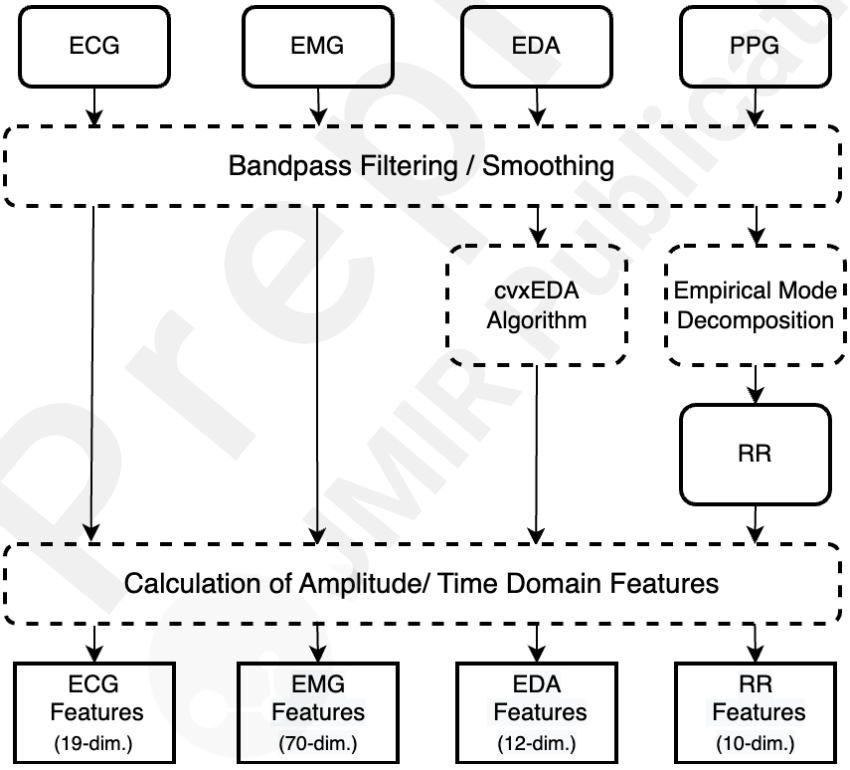


**Figure 1. Handcrafted feature extraction pipeline.**

## *Automatic Feature Extraction Pipeline*

As the dimensionality of biomedical data increases, it becomes increasingly difficult to train a machine learning algorithm on the entire uncompressed dataset. This often leads to a large training time and is computationally more expensive overall. One possible solution is to perform feature

engineering to get a compressed and interpretable representation of the signal. Another alternative approach, however, is to use the compressed or latent representation of that data obtained from deep learning networks trained for that specific task. Using automatic features helps in dimensionality reduction and can provide us with a sophisticated yet succinct representation of the data that HC features alone cannot provide. This automatic feature extraction is typically carried out by an autoencoder (AE) network, which is an unsupervised neural network that learns how to efficiently compress and encode the data into a lower-dimensional space [43, 44]. Autoencoders are composed of two separate networks, an encoder, and a decoder. The encoder network acts as a bottleneck layer and maps the input into a lower-dimensional feature space. The decoder network tries to reconstruct this lower-dimensional feature vector into the original input size. The entire network is trained to minimize the reconstruction loss (i.e., mean-squared error) by iteratively updating its weights and biases through backpropagation.

A convolutional AE from the pyEDA library was used to extract automatic features. Figure 2 shows the architecture of the AE. First, a linear layer (L1) is used to downsample the input signal with Input Shape length to a length that is the closest power of 2 (CP2). This was done to make the model scalable to an arbitrary input size. The encoder half of the network consists of three 1-D convolutional layers (C1, C2, and C3) and a linear layer (L2) which flattens and downsamples the input vector to a lower-dimensional latent vector. The number of dimensions of this latent vector (Feature Size) corresponds to the number of automatic features extracted and was set prior to training the network. A total of 32 features were extracted from ECG, EDA, and RR signals. Whereas a total of 30 features were extracted from the EMG signal (6 features from each of the 5 channels). The decoder half of the network consists of three 1-D de-convolutional layers (DeC1, DeC2, and DeC3) to reconstruct the input signal from the latent vector. A final linear layer (L3) is then used to flatten and reconstruct the signal to its original dimension. Both encoder and decoder networks have ReLU (Rectified Linear Unit) activation between layers. Window sizes of both 5.5 and 10 seconds were applied to the filtered signals. This was done to compare the performance with HC features. After signals from each of the modalities were normalized, they were trained on separate AE models for each modality. In addition to the convolutional AE, we also extracted features from an LSTM (long-short-term memory) AE network. This resulted in two different feature extraction methods (convolutional and LSTM) that spanned two different window lengths (5.5 and 10 seconds).

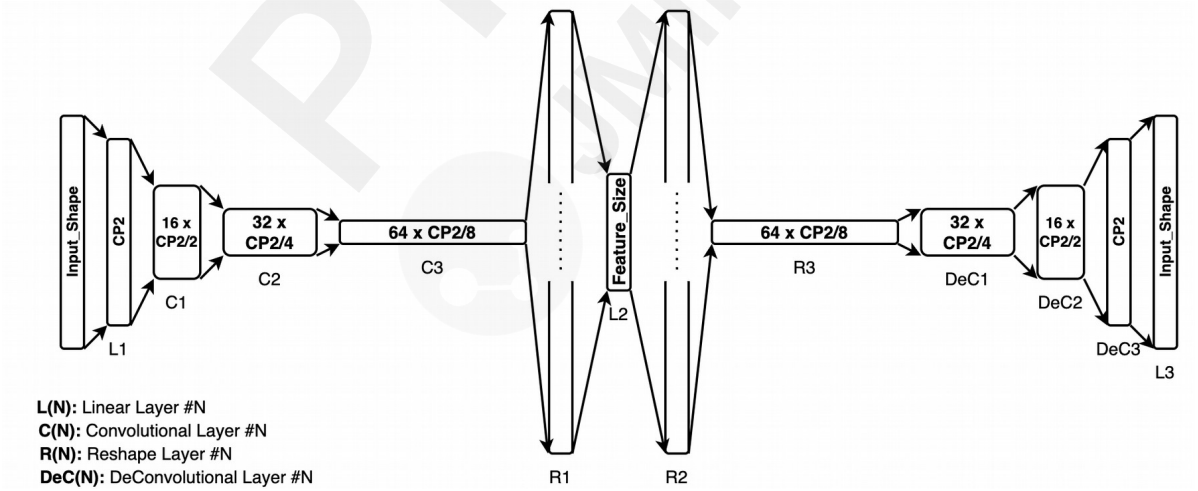


**Figure 2. The architecture of the pyEDA convolutional autoencoder.**

The batch size was set to 10, the number of training epochs was set to 100, and the ADAM optimizer [42] was used with a learning rate of 1e-3. A total of 126 feature vectors across all 4 modalities were

extracted from each AE network. A visualization of our automatic feature extraction pipeline is shown in Figure 3.

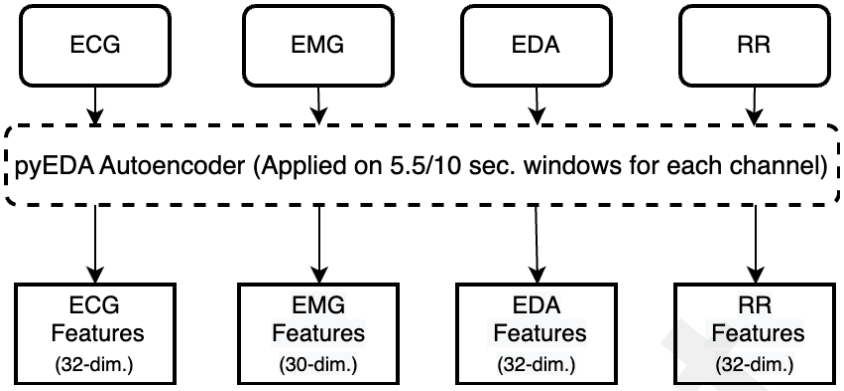


**Figure 3. Automatic feature extraction pipeline.**

## *Data Augmentation*

There were several inherent challenges in the distribution of labels as NRS values recorded during the clinical trials of this study were collected from real postoperative patients. This problem bears less significance while studying healthy participants since the stimulated pain can be controlled during the experiments. Consequently, occurrences of some pain levels far exceeded those of others. For example, among all patients, there were only 4 reported occurrences of pain level 10, whereas there were more than 80 reported occurrences of pain level 4. This imbalanced distribution was inevitable due to the subjective nature and the different sources of pain among the participants. Therefore, while downsampling our pain labels to 4 classes, thresholds for each downsampled class were carefully chosen to ensure a more evenly distributed set of labels. The pain levels ranged from a baseline level of pain (BL) or no pain to 3 increasing intensities of pain (PL 1-3). The thresholds for the pain levels were as follows - 1) PL1 ranged from 0 to 3, 2) PL2 ranged from 4 to 6, and 3) PL3 ranged from 7 to 10. All the ranges here are inclusive.

Since we asked patients to report their pain levels only while they performed pain-inducing activities, the number of labels generated was sparse. Both HC and automatic features were combined with the corresponding labels using timestamps that were within the nearest 5.5 or 10 seconds (labeling threshold) of the reported NRS value. This depended on the window size of the features extracted. Because of having sparse labels, many of the feature windows were not assigned a corresponding label. To mitigate the problem of having an imbalanced and sparse label distribution, two techniques were exploited:

**1) Minority Oversampling:**

The first technique, called Synthetic Minority Oversampling (Smote), is a type of data augmentation that over-samples the minority class [46]. Smote works by first choosing a minority class instance at random and finding its k nearest minority class neighbors. It then creates a synthetic example at a randomly selected point between two instances of the minority class in that feature space. The experiments involving Smote were implemented using the imbalanced-learn Python library [47].

**2) Weak Supervision:**

The second technique we utilized is weak supervision using the Snorkel framework [48].

Rather than employing an expert to manually label the unlabeled instances, Snorkel allows its users to write labeling functions that can make use of heuristics, patterns, external knowledge bases, and third-party machine learning models. Weak supervision is typically employed to label large volumes of unlabeled data when there are noisy, limited, or imprecise sources. For our pain assessment algorithm, we decided to use third-party machine learning models to label the remaining unlabeled instances. All the data points that were within the labeling threshold were considered as "strong labels", or ground-truth values collected from patients during trials. The remaining unlabeled data points were kept aside for Snorkel to provide a weakly supervised label. The strong labels were fed into Snorkel's labeling function consisting of three off-the-shelf machine learning models: (i) a Support-Vector Machine (SVM) with a radial basis function kernel, (ii) a Random Forest (RF) classifier, and (iii) a K-Nearest Neighbor (KNN) classifier with uniform weights. Once each model was trained on the strong labels, it was used to make predictions on the remaining unlabeled data. The predictions from these three models were collected and converted into a single confidence-weighted label per data point using Snorkel's "LabelModel" function. This function outputs the most confident prediction as the label for each data point. To perform a fair assessment of the reliability and accuracy of our algorithm, we used Smote and Snorkel only while training our machine learning models. The performance of these models was measured solely on ground-truth (strong) labels collected during trials. This way, there is no implicit bias introduced from mislabeling or upsampling certain data points to skew model predictions.

## *Multimodal Machine Learning Models*

To compare the performance of our multimodal machine learning models with the prior work, we performed binary classification using a leave-one-subject-out cross-validation approach [49]. In this method, a model's performance is validated over multiple folds in such a way that data from each patient is either in the training set or in the testing set. The purpose of using this method is to provide generalizability to unseen patients and to avoid overfitting by averaging the results over multiple folds. The eventual goal of this study is to build personalized models that make predictions on a single patient but learn from data collected from a larger population of similar patients. The following machine learning models were used to evaluate the performance of our pain assessment algorithm: (1) K-nearest neighbors, (2) Random Forest classifier, (3) AdaBoost (Adaptive Boosting), (4) and an SVM (Support Vector Machine). The models were then evaluated using leave-one subject-out cross-validation. Four separate models were trained for each of the three pain intensities (e.g., BL, no pain versus PL1, the lowest pain level, or BL vs PL3, the highest pain level).

## *Fusing Modalities*

Two fusion approaches were used while combining features across different modalities. The first one is early or feature-level fusion which concatenates feature vectors across different modalities based on their timestamps. The resulting data that is now higher in dimension than any one single modality is then fed into our classifier to make predictions. While concatenating features across different modalities, a threshold of either 5.5 or 10 seconds was used to combine the modalities depending on the features extracted. The second approach was late or decision-level fusion where each modality is fed to a separate classifier and the final classification result is based on the fusion of outputs from the different modalities [50].

### *Feature Selection*

Since there were a lot of features generated during the data processing phase, we had to select a subset of the most informative features to build our models with. Therefore, to reduce the complexity and training time of the resulting model, feature selection using Gini importance was performed. Gini importance is a lightweight method that is simple and fast to compute. Since we extracted a relatively large number of features in our method, it made sense to use a computationally low-cost algorithm for feature selection. We computed the Gini importance of the features from the data in the training fold with the help of a random forest classifier and selected the top 25 features. We then trained our model on these top 25 features and evaluated them in the validation fold. Our proposed multimodal pain recognition system is shown in Figure 4.

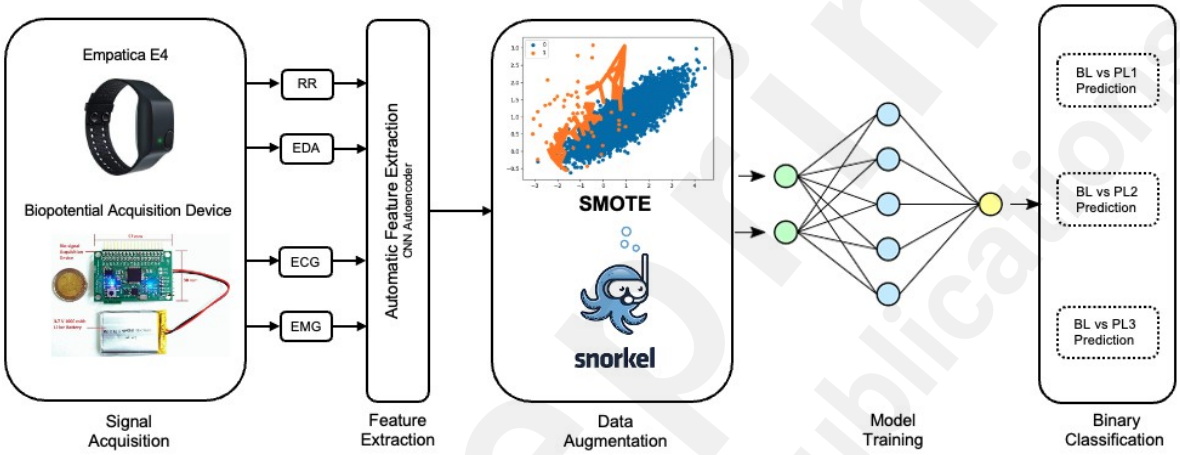


**Figure 4. Proposed multimodal pain recognition system.**

## Results

### *Experimental Settings*

The goal of our experiments was to compare the performance of using only a single modality to build our models over using a combination of multiple modalities. We trained several different models for each of the pain intensities that varied in the types of modalities, data augmentation techniques, machine learning models, and fusion techniques used. Figure 5 shows the general pipeline of the experiments we conducted. We first select the type of modalities to train on, which varied from only using each of the single modalities separately to using a combination of all 4 modalities. Moreover, these modalities varied on the types of features used, like HC or automatic features. In the case of using multiple modalities, we had two choices of fusion: early (Figure 5 left) and late (Figure 5 right). These architectures varied in how the modalities were combined, either before training (early), or at the decision level (late) after training using majority voting. The data preparation process involved feature selection and data augmentation. These models could either be trained with no data augmentation, with just Smote or Snorkel, or a combination of both. The last step of the pipeline before making predictions involved choosing the type of machine learning algorithms, like SVM, Random Forest (RF), Adaptive Boosting (AdaBoost), or K-Nearest Neighbors (KNN). Due to the lack of space, only the best-performing single and multimodal model configurations are mentioned in the section below.

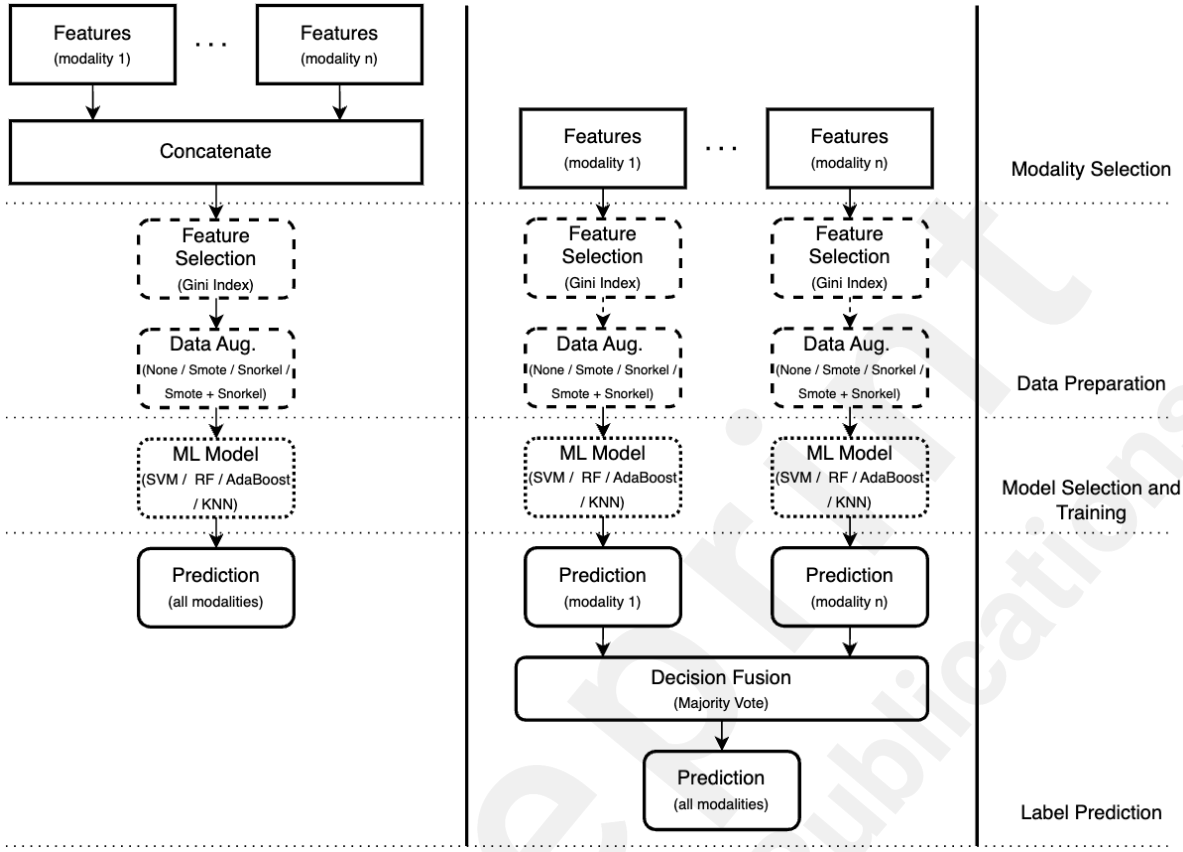


**Figure 5. Our proposed general multimodal pipeline based on early fusion (left) and late fusion (right).**

## *Experimental Results*

Tables 1 and 2 present the best-performing single-modal and multimodal models for each of the three pain intensities. For comparison, the best multimodal results from Werner et al. [17], Martinez et al. [24], Wang et al. [25], and Subramaniam et al. [26] are also mentioned. We use balanced accuracy as an evaluation criterion because our dataset had an imbalanced class distribution. Balanced accuracy is defined as the average of the true positive rate and the true negative rate.

**Table 1. Best scores: single modality vs multiple modalities**

| Pain Levels | ECG Scores | EMG Scores | EDA Scores | RR Scores | Multiple Modality |
|---|---|---|---|---|---|
| BL vs. PL1 | 82.14 | 86.0 | 79.18 | 84.62 | 82.14 |
| BL vs. PL2 | 86.11 | 84.53 | 82.94 | 88.24 | 86.11 |
| BL vs. PL3 | 75.0 | 78.12 | 75.0 | 76.23 | 75.0 |
| Mean | 81.08 | 82.88 | 79.04 | 83.03 | 81.08 |
| Classifier Config. | LSTM AE (10s), Strong, SVM | HC (10s), Snorkel, SVM | CNN AE (10s), Strong, SVM | HC (10s), Strong, SVM | EF, LSTM AE (10s), Strong, |

| | | | | | |
|---|---|---|---|---|---|
| | | | | | SVM |

**Table 2. Multiple modalities: comparison with other methods**

| | Werner et al. [17] | Martinez et al. [24] | Wang et al. [25] | Subramanian et al. [26] | Our Method |
|---|---|---|---|---|---|
| Mean | 65.27 | 66.84 | 70.28 | 76.28 | 81.08 |
| Modalities | Video, ECG, EMG, EDA | ECG, EMG, EDA | ECG, EMG, EDA | ECG, EDA | EDA, EMG, EDA, RR |

# Discussion

## *Principal Results*

From the single modality results (Table I), it is evident that RR models outperform all other modalities, especially for the BL vs PL1 and BL vs PL2 models. Overall, models from all modalities have relatively lower scores in the BL vs PL3 category. The comparatively lower performance of EDA models over other modalities suggests that variations in EDA signal response to different pain levels are more difficult to distinguish. From our experiments, the best-performing multimodal model was trained on automatic features outputted from our LSTM network with 10-second window size. This model made use of strong labels without any data augmentation techniques. It should be noted that the best-performing ECG and multimodal models have the same results and share identical configurations. It is very likely that the ECG features influenced the performance of the multimodal model.

The relatively poor performances of the BL vs PL1 and BL vs PL3 models across both single and multimodal models are also understandable because they lie at the extremes of the pain threshold. The BL vs PL1 models might find it more challenging to distinguish between baseline levels and the lowest pain intensity due to the subtlety of the physiological responses collected while experiencing this pain level. The BL vs PL3, however, might find it challenging to distinguish pain levels due to the scarcity of such labels collected during trials. Data augmentation can help mitigate this problem, but there is no substitute for real data. On the contrary, the BL vs PL2 models performed better due to the relative abundance of such labels reported during trials.

In terms of modalities, the best-performing model uses RR alone. However, for the last pain category, the EMG model outperformed all the other models. One justification for these results could be due to the dynamic nature of these signals in response to pain stimuli. Since we were able to effectively isolate and capture periods of higher pain intensity with smaller window sizes, this could help the models better distinguish between baseline and other pain levels.

The best-performing multimodal models use early fusion or feature-level fusion. One intuition as to why early fusion might perform better overall is due to the detection of correlated features across modalities obtained after using feature selection [51]. Late fusion, on the contrary, builds independent models for each modality and fuses them based on their predictions using majority voting. Therefore, by treating each modality as independent, there is a potential loss of correlation in the combined feature space.

Overall, the single modality results, specifically RR, outperform the multimodal models in all categories. This has not been the case in prior studies done on healthy subjects. But our experiments

suggest that a combination of multiple modalities in data collected from postoperative patients has the potential to skew results. Since there is a risk of missing data and noise in our signals, it is imperative to carefully align them when combining the modalities. Multiple modalities certainly have the potential to add more useful information over a single modality and can be used to introduce complementary information and resiliency when any one modality fails or is too noisy [52]. They are also more robust and can improve generalizability when patients experience different types of pain and in varying degrees. However, there are also advantages to using a single modality. They are simpler and easier to interpret when measuring each feature's contribution to the output. This also reduces computational complexity and training time. While comparing our results to [17, 24, 25, 26], it can be observed that our models outperform their models in mean pain assessment scores. However, this is not entirely a fair comparison because we use 3 pain levels instead of 4 and our patients are not healthy.

One of the main research directions we would like to explore in the future is to build real-time multimodal pain assessment systems using deep learning architectures. In such scenarios, it is quite possible to have missing or incomplete data from or more modalities. Moreover, real-time systems are limited by their computational complexity and power constraints. Therefore, with the help of the experiments performed in this study, we hope to build models that can dynamically determine which modalities to use in an energy-efficient manner without compromising performance given the clinical context.

## Limitations

The main limitation of our algorithm is the presence of noise in the form of motion artifacts produced while collecting physiological signals. Since we obtained data from real postoperative patients in a clinical setting, they were allowed to move more freely in comparison to experiments performed in laboratory settings. The presence of these motion artifacts diminished the quality of our data, and thus negatively impacted our machine-learning algorithms. We also must acknowledge the more complicated facets of pain that are not fully captured by our algorithm like the number of days post-surgery, the amount of pain medication dosing, the location, and the type of pain experienced. We would like to account for these factors while conducting future studies.

## Conclusions

In this paper, we presented a multimodal machine-learning framework for classifying pain in real post-operative patients from the iHurt Pain Database. Both traditional handcrafted features and deep learning-generated automatic features were extracted from physiological signals (ECG, EDA, EMG, PPG). We conducted several experiments to perform binary classification among three different pain intensities vs baseline levels of pain. Models for each of these intensities were varied based on the modalities used, the different types of data augmentation techniques (Smote, Snorkel, or both), the machine learning algorithms used, and the type of modality fusion used. Our results showed that binary pain classification greatly benefits from using data augmentation techniques in conjunction with automatic features. The single-modality models from RR and EMG outperformed the multimodal models. The BL vs PL3 model with the best results was trained on EMG data alone, which suggests that facial muscle activation can play a vital role in distinguishing higher pain intensities from baseline levels of pain. This is consistent from a clinical perspective because higher pain intensities are more commonly associated with acute pain.

However, since pain is a subjective experience that tends to have a large inter-individual variability, building a monolithic model for all patients might not be a viable solution. A promising future direction for this research study is to build personalized machine learning models that can benefit

from using data from groups of similar patients, but which are finetuned to make predictions on a single person. Prior research has used multitask machine learning (MTL) to account for inter-individual variability and build personalized models for the task of mood prediction [53]. This is a feasible future research direction that would be applicable to the domain of pain assessment, not only for the acute pain of surgery but also for patients that experience chronic pain. We believe that personalized modeling will be a vital step in creating clinically viable pain assessment algorithms.

## Conflicts of Interest

Non declared.

## Abbreviations

UCIMC: University of California Irvine Medical Center
NRS: Numerical Rating Scale
HRV: Heart Rate Variability
ECG: Electrocardiography
EMG: Electromyography
EDA: Electrodermal Activity
PPG: Photoplethysmography
RR: Respiration Rate
EMD: Empirical Mode Decomposition
PL: Pain Level
BL: Baseline
ML: Machine Learning
SVM: Support Vector Machine
RF: Random Forest
KNN: K-Nearest Neighbors
LSTM: Long-Short Term Memory
CNN: Convolutional Neural Network
AE: Auto Encoder
HC: Handcrafted
EF: Early Fusion
LF: Late Fusion

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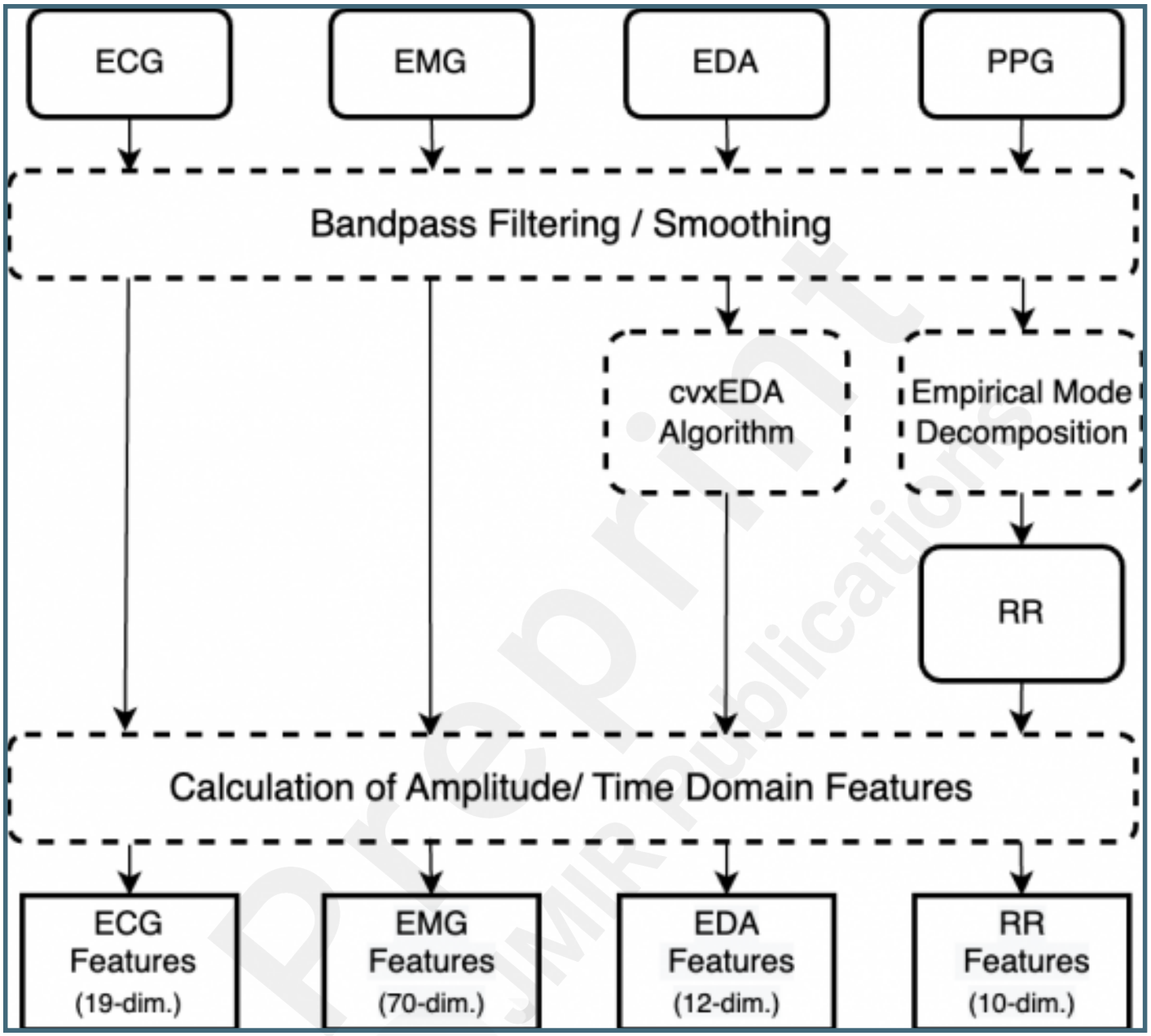
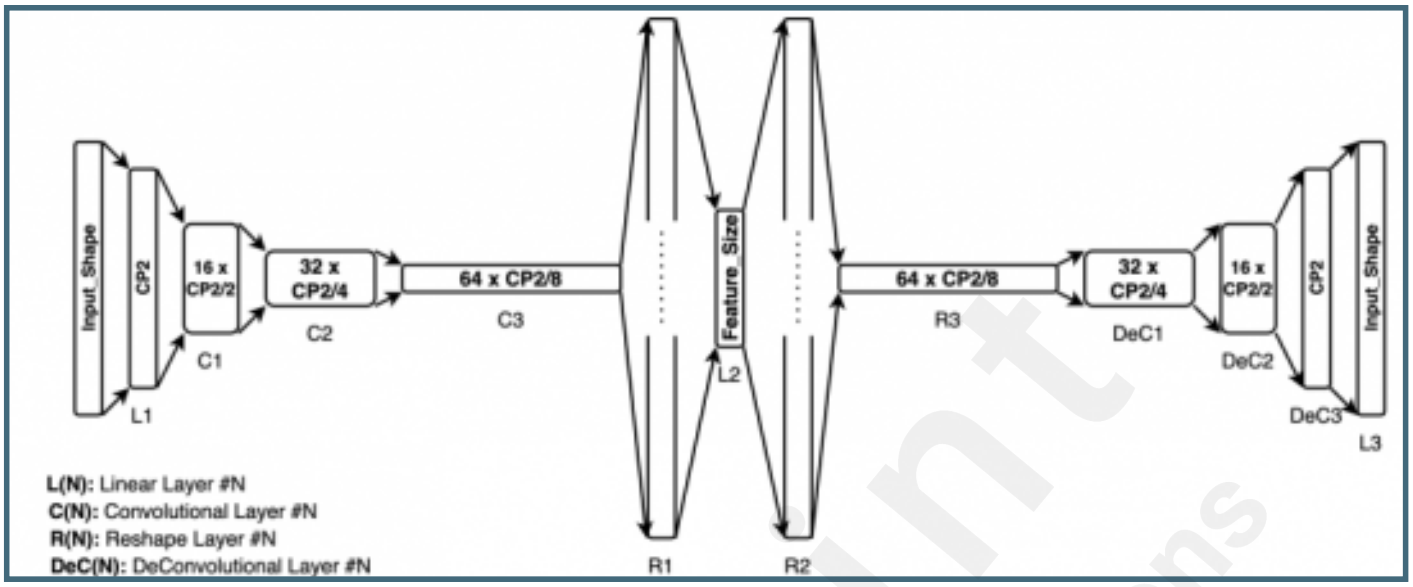
# Supplementary Files

# Figures

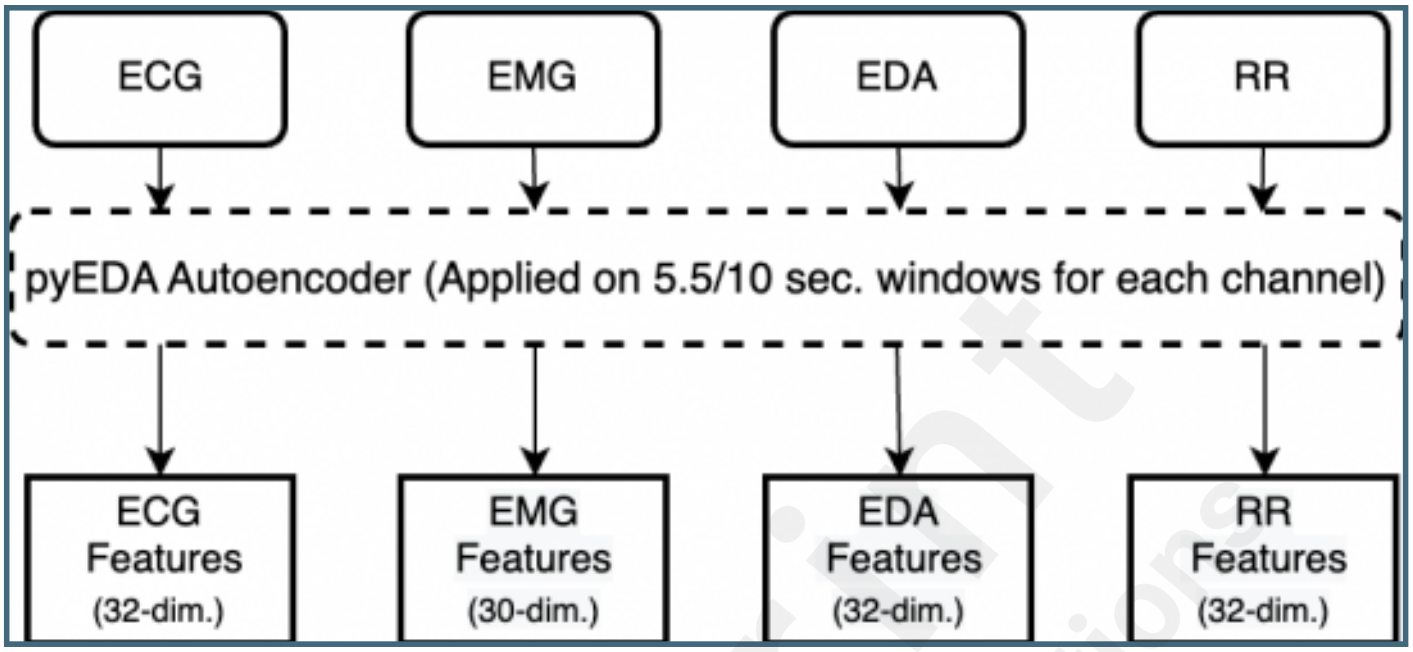
Handcrafted feature extraction pipeline.



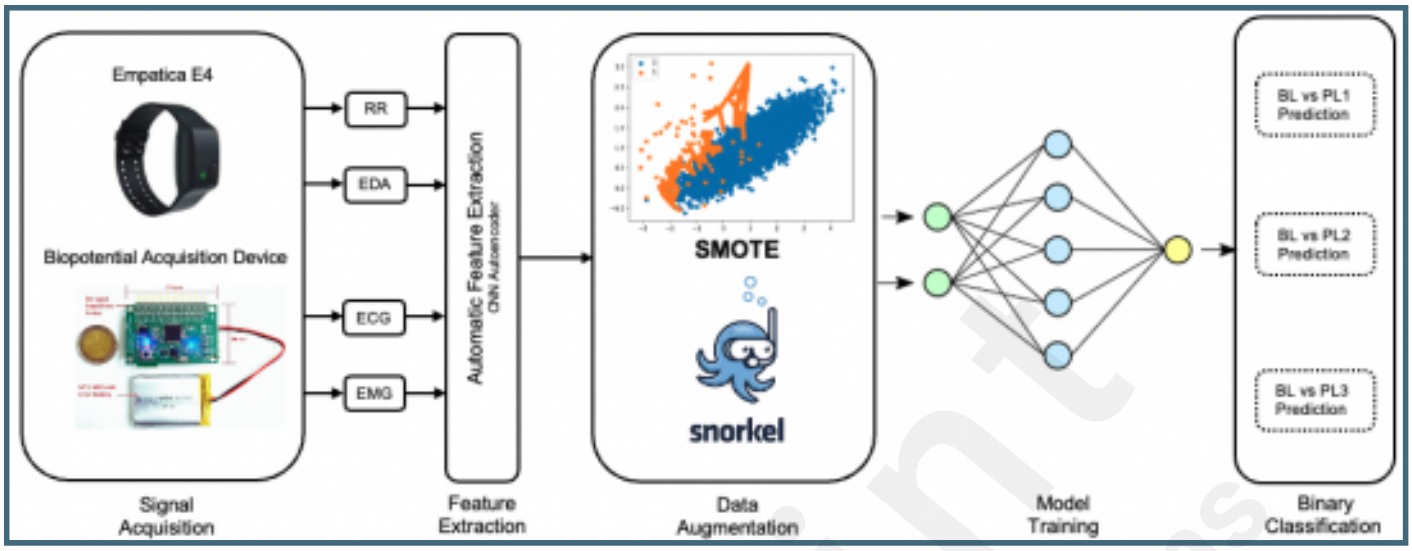
The architecture of the pyEDA convolutional autoencoder.



Automatic feature extraction pipeline.



Proposed multimodal pain recognition system.



Our proposed general multimodal pipeline based on early fusion (left) and late fusion (right).