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Pain Hybrid Model for Pain Recosnitionusins CNN+BL-LSTM+BL-SRU

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Abstract: **Pain is one of the most frequent symptoms experienced by patients in a clinical environment. Automatic pain recognition systems are developed to support medical personnel in assessing and interpreting a patient's pain level. In this paper, we propose a system for pain recognition using physiological signals such as ECG (Electrocardiogram), EMG (Electromyogram), and SCL (Skin Conductance Level). These signals are recorded from subjects who are subjected to pain-inducing stimuli. The signals are preprocessed and analyzed to extract relevant features. Machine learning algorithms are then applied to classify the pain levels. The proposed system achieves promising results, suggesting that physiological signals can be effectively used for automatic pain detection. This can lead to better pain management and improved patient care. This project addresses the need for automatic pain recognition in healthcare without relying on expert feature extraction from physiological signals. Instead, it introduces a deep learning approach that combines feature extraction and classification. The method incorporates multi-level context information for accurate pain discrimination. Experimental results, based on datasets like BioVid Heat Pain and Emopain 2021, demonstrate its superiority over conventional methods.**

INTRODUCTION

Pain assessment is a critical aspect of patient care in medical settings. However, traditional pain evaluation methods often rely on patients' self-reporting, which may not always be possible—especially in cases involving infants, unconscious patients, or individuals with communication impairments. To overcome these limitations, researchers are turning towards automatic pain recognition systems that use physiological signals to detect and assess pain levels objectively.

This project focuses on developing a system that uses physiological signals such as Electrocardiogram (ECG), Electromyogram (EMG), and Skin Conductance Level (SCL) to recognize pain. These signals are recorded from subjects exposed to controlled pain stimuli. The signals are then preprocessed, and significant features are extracted to feed into machine learning models that classify pain intensity.

By utilizing physiological data, this system aims to provide an objective and continuous method for pain assessment. It holds potential applications in hospitals and eldercare facilities, enhancing the quality of care through accurate and timely pain detection.

Pain, a crucial indicator of illness, often relies on subjective human assessment, limiting its universality. Automating pain recognition becomes imperative in healthcare. Traditional methods, reliant on observations and individual interpretations, lack universal standards. Physiological signals, including skin conductance, heart rate variability, and EEG, offer objective measures for pain assessment. However, recognition through patient behavior remains unreliable. Physiological signals' alterations due to pain responses present promising avenues. The BioVid Heat Pain Database popularized signals like EDA, ECG, and EMG for pain recognition. This research explores leveraging deep learning on physiological signals, aiming to automate pain recognition, circumventing the limitations of behavior-based assessments in healthcare.

PROPOSED SYSTEM

In this section, we introduce the materials for the proposed method. We introduce the definitions of multi-level context information on physiological signals in pain intensity recog nition. Firstly, we recommend architectures suitable for physiological signals including spatial and temporal architectures.

The proposed system for pain recognition is designed to automatically detect and classify pain levels using physiological signals such as Electrocardiogram (ECG), Electromyogram (EMG), and Skin Conductance Level (SCL). The process begins with data acquisition, where these signals are collected from subjects exposed to controlled pain stimuli. The raw signals are then preprocessed to remove noise and artifacts using filtering and normalization techniques. Once the signals are cleaned, meaningful features are extracted—such as mean, variance, and other statistical values—which represent the body's physiological response to pain. These features are then fed into machine learning algorithms like Support Vector Machines (SVM), Random Forest, or Neural Networks, which are trained to classify the pain levels based on the patterns in the data. The final output of the system indicates the predicted pain intensity, which can assist healthcare professionals in monitoring and managing patient pain more effectively, especially in situations where verbal communication is not feasible.

SPATIAL ARCHITECTURE

Inspired by previous studies on the breakthrough perfor mance of deep learning networks, the proposed architec ture is built to emphasize the classification performance of deep learning networks and minimize dependence on manual designs. The work of expertise in medicine is precisely hand crafted features of physiological signals. This is employed automatically in deep learning with hierarchical layers that carry optimal parameters and weights. In deep learning, Convolutional Neural Networks (CNN) are widely used and highly effective networks for classifica tion tasks. The pooling layers reduce the number of parame ters to improve the calculation speed and avoid over-learning while preserving essential characteristics. Non-linearity is necessary to create non-linear decision boundaries between the output and the input, which partly helps CNN make breakthroughs. Weoptanon-linear activation function named Exponential Linear Unit (ELU) instead of ReLU to retain negative values. The Exponential Linear Unit (ELU) activa tion function is performed elementwise on every value from the input to saturate to a negative value when the argument gets smaller. Also, it reduces the vanishing gradient effect. In this study, we implement CNN with ELU activation to retain the negative values of feature maps. Then, we perform Instance Normalization to normalize all features of one chan nel. Finally, the feature maps are averagely pooled to reduce the spatial resolution. A simple spatial architecture designed for physiological signals

TEMPORAL ARCHITECTURE

Recurrent Neural Network (RNN) is not inferior to CNN in many aspects of deep learning networks. RNNs are also widely used and highly effective in tasks. However, RNN has someerrors in back propagation but Long short-term memory (LSTM) overcomes this disadvantage. Currently, this type of architecture is popular and widely used. In unidirectional LSTM, the hidden state carries contextual information from the backward to the forward direction in a unidirectional manner. Bidirectional LSTM is a sequence processing model that carries two LSTM directions: forward and backward. This helps BiLSTMs effectively increase the amount of infor mation available to the network. Therefore, BiLSTMs help extract temporal information and capture context information as a time series of physiological signals.

BAHDANAU VARIANT ATTENTION

The use of attention mechanisms in neural networks has brought great success in many tasks. The main idea of the attention mechanism is to focus on some relevant details and ignore the rest selectively. Attention is a mechanism that allows us to highlight different regions on an image The attention mechanism also aids in focusing correlated words in a sentence. In deep learning, attention constructs a vector whose values are important weights. These weights determine the amount of attention we should pay to each hidden state to generate the desired output. In [22], Bahdanau et al. proposed neural machine trans lation with a novel architecture using an encoder-decoder approach. The authors implement an attention mechanism that incorporates the hidden state of RNN to extract context vectors in the decoder. For each word, the context vector is computed as the weighted sum of annotation. Each attention weight is obtained by normalizing each energy score with a softmax function, thereby determining the amount of atten tion that should be paid to each hidden state to produce the desired output. The energy score is built on the alignment function of the previous hidden state and the annotation. The annotation of each word is obtained by concatenating the forward and backward hidden states. Efficient use of the weighted sum of these annotation shelpscon text vectors carry more selective context information than hidden states. Inspired by the Bahdanau attention mechanism, we pro pose a variant of the Bahdanau attention mechanism for pain recognition tasks. The idea of variation is based on separately constituting two context vectors with attention weights from the last forward and backward states. Combining the two context vectors provides more contextual information regarding the input sequence.

MULTI-LEVEL CONTEXT INFORMATION

This section introduces a method capable of extracting multi level representations from context information. We first per form standardization as a preprocessing step. After being preprocessed, each physiological signal modality, as shown in Figure 1, is fed into the Instance Normalization layer to normalize the input layer. After normalization, each output is fed into a CNN block to extract spatial information. Concur rently, the pooling layers are used to reduce spatial resolution. The output of the CNN block is connected to the BiLSTMs and Bahdanau Variant Attention in the level blocks.

Levels of blocks are built based on the fluctuating informa tion of the last hidden information, as it plays a pivotal role in creating the context information. In this work, we choose the classification of Pain 0 and Pain 4 to illustrate, that other classification tasks have similar analyses. The last hidden information of EDA and ECG for the classification Pain 0 and Pain 4 are illustrated in Figure 4 and Figure 5. High level values have larger fluctuations and deviations than the remaining levels. It is similar to Middle Level and Low Level. Weimplement scaling to expand the last hidden information at the High Level and compress it at the Middle Level and Low Level before feeding it to the attention module.

IMPLEMENTATION DETAILS

This network is trained with python programming language using Keras on Tensor flow version 2.7. Adam optimization [23] is performed to optimize the binary cross-entropy loss function. For Part A of the BioVid Heat Pain database, we use leave-one-subject-out (LOSO) cross-validation to improve the comparability of recognition performances. The performances are estimated with LOSO on all the available subjects in the dataset. In [5], the authors propose a subject subset of 20 that excludes participants as noise subjects because they do not respond clearly to applied pain stimuli. So, LOSO cross-validation is conducted with the remaining 67 subjects. We train 50 epochs with 64 samples for the batch

LITERATURE REVIEW

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METHODOLOGY AND WORKING

1. Data Acquisition

This is the foundational step where physiological signals are collected from human subjects. Devices such as ECG sensors (to measure heart activity), EMG sensors (to measure muscle activity), and skin conductance sensors (to measure sweating and emotional arousal) are used. These sensors are noninvasive and capture the body's involuntary responses to pain stimuli. The data is typically recorded during specific pain-inducing tasks or stimuli (like pressure, heat, or cold) under controlled conditions. The collected data is timestamped and stored for further processing.

2. Preprocessing
Raw physiological signals are usually noisy and can include motion artifacts, baseline drift, and electrical interference. This module applies techniques such as:

- Band-pass filtering to remove unwanted frequencies,
- Normalization to standardize data across different individuals,
- Smoothing to eliminate sharp, irregular peaks.

Preprocessing is crucial because noise in physiological signals can mislead the classification model. A clean and consistent dataset ensures that the features extracted in the next stage are accurate and meaningful.

3. Feature Extraction
Once the signals are preprocessed, key features are extracted. These features act as numerical representations of the pain response. Common features include:

- Time-domain features: Mean, variance, standard deviation, peak-to-peak amplitude.
- Frequency-domain features: Power spectral density, dominant frequency.
- Signal complexity features: Entropy, signal energy.

Each physiological signal type (ECG, EMG, SCL) may provide unique features that contribute to recognizing pain. The extracted feature vectors are then compiled into a dataset that serves as input for the classifier.

4. Classification
This module uses machine learning algorithms to analyze the features and determine the pain level. Some commonly used models include:

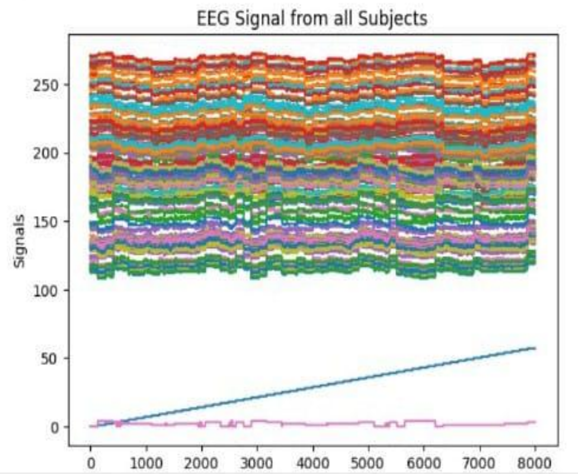
- Support Vector Machines (SVM): Effective for binary and multi-class classification with clear margin separation.
- Random Forest: A robust ensemble model that handles overfitting and noisy data well.
- Neural Networks: Especially useful for complex, non-linear relationships in large datasets.

The model is trained using labeled data, where pain levels are already known. After training, the classifier can predict pain levels on new, unseen data. The model performance is typically evaluated using metrics like accuracy, precision, recall, and F1-score.

5. Output Display
The final output from the classification model is a predicted pain level (e.g., "No Pain", "Mild Pain", "Severe Pain"). This result is displayed on a user interface or stored in a database for medical staff to review. In a real-time setup, this module could be connected to a monitoring dashboard in hospitals or clinics, enabling timely and objective pain assessment. It could also be integrated with alert systems to notify caregivers when patients experience high pain levels.

RESULT

EEG Signal from all Subjects:



CONCLUSION

This paper proposes a deep learning approach based on physiological signals for pain recognition. Our method has the role of feature extraction and classification, completely replacing manual extraction methods that require highly specialized knowledge. We propose multi-level context information explored from hidden sequence information. Specifically, the architecture employs hidden information for the attention mechanism to create the context vector. We combine hidden information and context vector to create the context information. Combining context information at three levels produces multi-level context information. We perform binary classification between baseline and different pain intensities based on Part A of the BioVid Heat Pain database. In addition, we also perform binary classification based on the Emopain

2021 dataset. Our experimental results prove that multi-level context information has more significance than uni-level context information based on Part A of the BioVid Heat Pain database and the Emopain 2021 dataset. Our results demonstrate the great significance of EDA in pain classification. Combining EDA and ECG mostly provides good performance in classification tasks based on Part A of the BioVid Heat Pain database. In summary, the deep learning approach has superior potential to replace previous conventional methods in pain recognition tasks. The exploration of hidden information in the physiological signal sequence provides significant performance for classification tasks.

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