Pain Recognition with Physiological Signals Using Multi-Level Context Information

Dr.CHANDRA MOHAN

[1] Assistant Professor,Malla Reddy Engineering College for Women (Autonomous Institution), Hyderabad, gaya3pillutla@gmail.com

[2],[3],[4]Student,Malla Reddy Engineering College for Women (Autonomous Institution),Hyderabad.

challaharshini2003@gmail.com[2], anampallyvaishnavi9@gmail.com[3]

sahgrply@gmail.com[4]

Abstract:

Automatic pain recognition is essential in healthcare. In previous studies, automatic pain recognition methods preferentially apply the features extracted from physiological signals for conventional models. These methods provide good performance but mainly rely on medical expertise for feature extraction of physiological signals. This paper presents a deep learning[1] approach based on physiological signals that have the role of both feature extraction and classification, regardless of medical expertise. We propose multi-level context information for each physiological signal discriminating between pain and painlessness. Our experimental results prove that multi-level context information performs more significantly than unit-level context information based on Part A of the Bovid Heat Pain database[2] and the Mopani 2021 dataset. For Part A of the Bovid Heat Pain database, our experimental results for pain

recognition tasks include Pain 0 and Pain 1, Pain 0 and Pain 2, Pain 0 and Pain 3, and Pain 0 and Pain 4. In the classification task between Pain 0 and Pain 4, the results achieve an average accuracy of 84.8 B1 13.3% for 87 subjects and 87.8 B1 11.4% for 67 subjects in a Leave-One-Subject-Out cross-validation evaluation. The proposed method adopts the ability of deep learning to outperform conventional methods on physiological signals.

INTRODUCTION:

Pain is the body's common response to illness that requires medical attention. Traditional pain recognition methods are generally through human observations and subjective recognition. The physiotherapists assess a patient's pain through exercises during the therapy process and give reasonable exercises to the patient to overcome the disease. Pain recognition[3] depends on the knowledge of each expert, observation, and individual perception through the patient's expression. This brings many limitations because there are no universal and reliable rules for pain recognition. Therefore, the automation of pain recognition is necessary for humans. In the medical, pain recognition applications is a health monitoring system that helps humans recover from illness through physical therapy exercises. Pain recognition systems use behaviour and physiology to perform classification tasks. Measures are physiological signals, facial expressions, body movements, vocalizations, and so on, or a combination of them. In some cases, pain recognition through the patient's behaviour is not reliable. The patient can intentionally control emotional expression. Furthermore, the patients express pain behaviour depending on their personality. Some patients lose awareness and do not express painful emotions clearly and reliably. It is difficult to recognize pain through emotional behaviour. Therefore, pain recognition using physiological signals[4] as essential .Pain causes the response of the relevant neural structures and alters the measures of differences in physiological signals. Measures of physiological signals related to pain response such as skin conductance, heart rate variability, resting blood pressure, and electroencephalography (EEG). Skin conductance is a signal in response to pain. The increased sympathetic outflow associated with pain secretes the sweat on the skin's surface. This is the factor to increase electrodermal activity (EDA). The increased sympathetic activity also affects heart rate, increasing heart rate variability or resting blood pressure. In addition, pain affects metabolic areas in the cerebral cortex, or muscle activity. Since the publication of the Bovid Heat Pain Database, EDA and electrocardiogram (ECG) and (electromyogram) EMG signals have become widely used for pain recognition. EDA signals show the skin conductance level, ECG represents the action potential of heart rate and the EMG signal measures muscle activity.The task of automatic pain[5] classification remains extremely challenging. Many previous studies evaluating pain use tools to extract the dynamic characteristic composition of physiological signals to facilitate classification. The efficient methods use representations of physiological signals selected carefully based on medical expertise. The representations include relevant information extracted from the raw data They represent as numeric feature vectors. The set of robust representations can describe the information of the entire data with a size smaller than that of the raw data. These robust representations are fed into inference models and provide fairly high performance. This proves that the skill of selecting representations in machine learning is very necessary for improving the classifier's performance. It is difficult to take advantage of robust representations because they depend on specialized knowledge of raw datasets. This causes time-consuming self-study and the cost of hiring experts to build robust representations. These studies neglect the powerful automated capabilities of the design model.Deep learning approaches automatically generate suitable representations of raw data. Deep learning architecture is a multi-layer stack of simple modules that can learn and compute non-linear mappings. They entirely replace classical methods and do not depend on specialized knowledge of physiological signals. This study aims to build a deep learning model to replace the conventional methods which rely on expert knowledge of physiological signals. It is possible to eliminate the hand-crafted feature selection carefully. We experiment by extracting contextual representation from physiological signals[6] which have stationery and trending factors. Our idea is to build a contextual representation from the hidden information on a sequence in physiological signals. Contextual representation is the time series characteristics of physiological signals for pain or non-pain manifestations. In this study, the context representations are named multi-level context information.Pain recognition is a binary classification that distinguishes painful and non-painful manifestations. In this work, we evaluate the performance of the proposed model based on Part A of the bovid Heat Pain Database and the mopani 2021 dataset. Our method uses simple pre-processed physiological signals that are available in the datasets.Part A of the bovid Heat Pain database consists of five classes with four painful classes and a baseline class representing a non-painful class. In particular, we perform four classification tasks with each task being a classification between each painful class and baseline class. Our model applies the ability to capture spatial information and reduce spatial resolution while preserving the important characteristics of Convolutional Neural Networks. The model continues to use the Recurrent Neural Network's ability to extract hidden information. We then propose a combination of multiple levels of context information. As shown in the EDA and ECG illustrations in columns a) and b) of the signals through pain levels affect the stationary and the trending of the time series. Therefore, we choose the combination of EDA and ECG signals without EMG signals. We coordinate multi-level context information from EDA and ECG physiological signals.

Related works:

.‘‘Automatic recognition methods supporting pain assessment: A survey,’’

Pain is a complex phenomenon, involving sensory and emotional experience, that is often poorly understood, especially in infants, anesthetized patients, and others who cannot speak. Technology supporting pain assessment has the potential to help reduce suffering; however, advances are needed before it can be adopted clinically. This survey paper assesses the state of the art and provides guidance for researchers to help make such advances. First, we overview pain’s biological mechanisms, physiological and behavioural responses, emotional components, as well as assessment methods commonly used in the clinic. Next, we discuss the challenges hampering the development and validation of pain recognition technology, and we survey existing datasets together with evaluation methods. We then present an overview of all automated pain recognition publications indexed in the Web of Science as well as from the proceedings of the major conferences on biomedical informatics and artificial intelligence[7] to provide understanding of the current advances that have been made. We highlight progress in both non-contact and contact-based approaches, tools using face, voice, physiology, and multi-modal information, the importance of context, and discuss challenges that exist, including identification of ground truth. Finally, we identify underexplored areas such as chronic pain and connections to treatments, and describe promising opportunities for continued advances.

‘‘The bovid heat pain database data for the advancement and systematic validation of an automated pain recognition system,’’

The objective measurement of subjective, multi-dimensionally experienced pain is still a problem that has yet to be adequately solved. Though verbal methods (i.e., pain scales, questionnaires) and visual analogue scales are commonly used for measuring clinical pain, they tend to lack in reliability or validity when applied to mentally impaired individuals. Expression of pain and/or its biopotential parameters could represent a solution. While such coding systems already exist, they are both very costly and time-consuming, or have been insufficiently evaluated with regards to the theory of mental tests. Building on the experiences made to date, we collected a database using visual and biopotential signals to advance an automated pain recognition system, to determine its theoretical testing quality, and to optimize its performance.

For this purpose, participants were subjected to painful heat stimuli under controlled conditions.

‘‘The affect move 2021 challenge—Affect recognition from naturalistic movement data,’’

We ran the first Affective Movement Recognition (Affect Move) challenge that brings together datasets of affective bodily behaviour across different real-life applications to foster work in this area. Research on automatic detection of naturalistic affective body expressions is still lagging behind detection based on other modalities whereas movement behaviour modelling is a very interesting and very relevant research problem for the affective computing community. The Affect Move challenge aimed to take advantage of existing body movement datasets to address key research problems of automatic recognition of naturalistic and complex affective behaviour from this type of data. Participating teams competed to solve at least one of three tasks based on datasets of different sensors types and real-life problems: multimodal Mopani dataset for chronic pain physical rehabilitation context, we Draw-l Movement dataset for maths problem solving settings, and multimodal Unite-Maastricht Dance dataset. To foster work across datasets, we also challenged participants to take advantage of the data across datasets to improve performances and also test the generalization of their approach across different applications.

‘‘Methods for person-cantered continuous pain intensity assessment from biophysiological channels,’’

In this work, we present methods for the personalization of a system for the continuous estimation of pain intensity from bio-physiological channels. We investigate various ways to estimate the similarity of persons and to retrieve the most informative ones using meta-information, personality traits, and machine learning techniques. Given this information, specialized classifiers can be created that are both, more efficient in terms of complexity and training times and also more accurate than classifiers trained on the complete data. To capture the most information in the different bio-physiological channels, we cover a broad spectrum of different feature extraction algorithms. Furthermore, we show that the system is capable of running in real-time and discuss issues that arise when dealing with incremental data processing. In extensive experiments we verify the validity of our approach.

‘‘The use of multiple measurements in taxonomic problems,’’

The Annals of Human Genetics has an archive of material originally published in print format by the Annals of Eugenics (1925-1954). This material is available in specialised libraries and archives. We believe there is a clear academic interest in making this historical material more widely available to a scholarly audience online. These articles have been made available online, by the Annals of Human Genetics, UCL and Blackwell Publishing Ltd strictly for historical and academic reasons. The work of eugenicists was often pervaded by prejudice against racial, ethnic and disabled groups. Publication of this material online is for scholarly research purposes is not an endorsement or promotion of the views expressed in any of these articles or eugenics in general. All articles are published in full, except where necessary to protect individual privacy. We welcome your comments about this archive and its online publication.

‘‘Boost: A scalable tree boosting system,’’

Tree boosting is a highly effective and widely used machine learning method. In this paper, we describe a scalable end-to-end tree boosting system called Boost, which is used widely by data scientists to achieve state-of-the-art results on many machine learning challenges. We propose a novel sparsity-aware algorithm for sparse data and weighted quantile sketch for approximate tree learning. More importantly, we provide insights on cache access patterns, data compression and sharding to build a scalable tree boosting system. By combining these insights, boost scales beyond billions of examples using far fewer resources than existing systems.

‘‘Personalized deep bi-LSTM RNN based model for pain intensity classification using EDA signal,’’

Automatic pain intensity assessment from physiological signals has become an appealing approach, but it remains a largely unexplored research topic. Most studies have used machine learning approaches built on carefully designed features based on the domain knowledge available in the literature on the time series of physiological signals. However, a deep learning framework can automate the feature engineering step, enabling the model to directly deal with the raw input signals for real-time pain monitoring. We investigated a personalized Bidirectional Long short-term memory Recurrent Neural Networks (Belts RNN), and an ensemble of Belts RNN and Extreme Gradient Boosting Decision Trees (XGB) for four-category pain intensity classification. We recorded Electrodermal Activity (EDA) signals from 29 subjects during the cold pressor test. We decomposed EDA signals into tonic and phasic components and augmented them to original signals. The Belts-XGB model outperformed the Belts classification performance and achieved an average F1-score of 0.81 and an Area Under the Receiver Operating Characteristic curve (AUROC) of 0.93 over four pain states: no pain, low pain, medium pain, and high pain. We also explored a concatenation of the deep-learning feature representations and a set of fourteen knowledge-based features extracted from EDA signals. The XGB model trained on this fused feature set showed better performance than when it was trained on component feature sets individually. This study showed that deep learning could let us go beyond expert knowledge and benefit from the generated deep representations of physiological signals for pain assessment.

Methodology:

Propose work consists of following modules

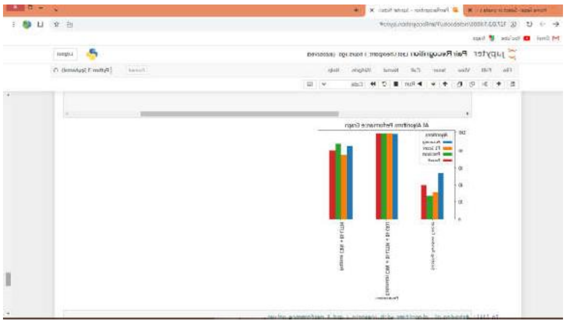
Upload Dataset: Using This Module,we will upload the dataset into the Application.

Preprocess Dataset: Using This Module,we will dataset is pre-processed.

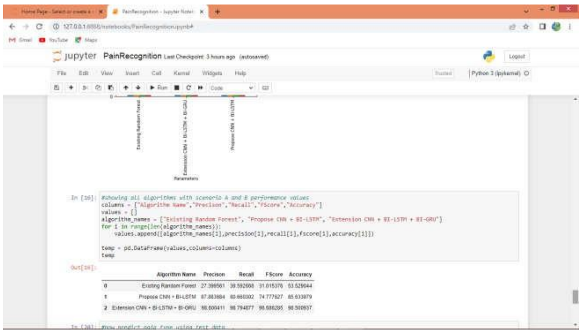
Run Calculate Metrices: Using This Module We will run the Calculate Metrices Algorithm.

Run Random Forest Algorithm: Using This Module We will run the Random Forest Algorithm.

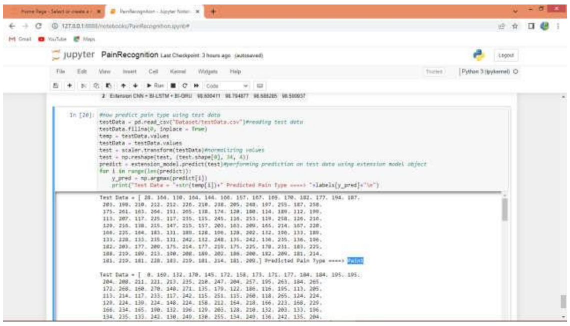
RESULTS:



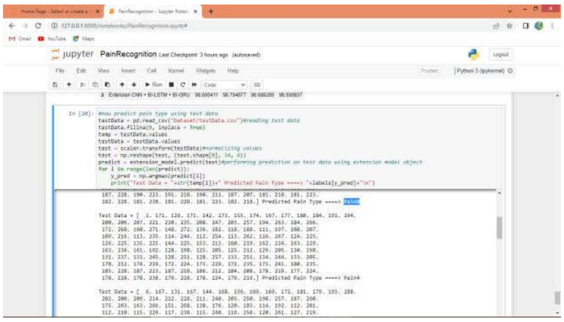
In above graph x-axis represents algorithm names and y-axis represents accuracy and other metrics in different colour bars and in all algorithms, Extension got high accuracy



In above screen displaying all algorithm performance in tabular format



Above code reading test data from file and then normalizing and predicting pain type using extension model and in output before =➔ symbol we can see ECG test data and after =➔ arrow symbol we can see predicted PAIN type. In above screen predicted pain type showing in blue colour



In above screen can see other predicted pain type

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 bovid Heat Pain database. In addition, we also perform binary classification based on the Mopani 2021 dataset. Our experimental results prove that multi-level context information has more significance than unit-level context information based on Part A of the bovid Heat Pain database and the mopani 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 bovid Heat Pain database.

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[3] Review analysis system using collective blended mechanism,ISSN: 2096-3246, Volume 55, Issue 01, April, 2023, Advanced Engineering ScienceDR. G. KALPANA1 , SHREYA2 , ANUHYA3 , SUSHMITHA4 1ASSOSCIATE PROFESSOR, DEPARTMENT OF CSE,
Malla Reddy Engineering College For Women, Hyderabad., Department Of Cse, Malla Reddy Engineering College For Women, Hyderabad

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