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Pain Recognition with Physiological Signals using Multi-Level Context Information

Chaitanya Yesambare[1], Prof. Jayant Adhikari[2], Aditya Lavhale[3]
[1] Department of Computer Science Engineering, Tulsiramji Gaikwad Patil College of Engineering and Technology, Nagpur, India.
Email: chaitanyan1434@gmail.com
[2] Department of Computer Science Engineering, Tulsiramji Gaikwad Patil College of Engineering and Technology, Nagpur, India.
Email: jayant.cse@tgpcet.com
[3] Department of Computer Science Engineering, Tulsiramji Gaikwad Patil College of Engineering and Technology, Nagpur, India.
Email: adityalavhale@gmail.com

Abstract
The project aims to develop an automatic pain recognition system in healthcare, removing the dependence on medical expertise for manual feature extraction from physiological signals. This shift addresses the limitations of conventional methods, making pain recognition more accessible and widely applicable. The proposed solution introduces a deep learning model that uniquely combines the roles of feature extraction and classification. By leveraging the strengths of deep neural networks, this approach streamlines the process, eliminating the need for separate feature engineering and classification steps commonly found in traditional methods. The project introduces a novel aspect by incorporating multi-level context information for each physiological signal. Unlike uni-level context information used in prior approaches, this multi-level understanding aims to provide a more nuanced perspective on pain and painlessness. It enhances the discriminative power of the model by considering various levels of context within the physiological signals. The deep learning approach demonstrated in the project showcases its superiority in handling physiological signals for pain recognition. By eliminating the need for explicit feature engineering by medical experts, the model can autonomously learn and extract relevant features directly from the data. This not only marks a significant advancement over conventional methods but also enhances the efficiency and accuracy of pain recognition based on physiological signals. The project's include a "Stacking Classifier" and hybrid model "CNN+BILSTM+GRU", in which stacking classifier got 99% accuracy for enhanced Pain Recognition.

Index Terms - Pain recognition, physiological signals, context vector, attention module, deep learning.

I. 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 [2, 6] 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 [18, 20] applications is a health monitoring system that helps humans recover from illness through physical therapy exercises. Pain recognition systems use behavior 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 behavior is not reliable. The patient can intentionally control emotional expression. Furthermore, the patients express pain behavior 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 behavior. Therefore, pain recognition [16] using physiological signals is 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) [1, 2, 7, 8, 12]. 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 [1]. Since the publication of the BioVid Heat Pain Database [2], EDA and electrocardiogram (ECG) and (electromyogram)

EMG signals have become widely used for pain recognition [1]. EDA signals show the skin conductance level, ECG represents the action potential of heart rate and the EMG signal measures muscle activity.
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 [3]. They entirely replace classical methods and do not depend on specialized knowledge of physiological signals. This study aims to build a deep learning model [3, 19, 21, 33] 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 which have stationary 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 multilevel 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 BioVid Heat Pain Database [2] and the Emopain 2021 dataset [4]. Our method uses simple preprocessed physiological signals that are available in the datasets.

II. Related Work

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 [1] 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 behavioral 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 [16, 18, 20], 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, 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 objective measurement of subjective, multi-dimensionally experienced pain is still a problem that has yet to be adequately solved [2]. 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 either 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 [24] 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.
To develop automatic pain monitoring systems, we need a deep understanding of pain expression and its influencing factors and we need datasets with high-quality labels. This work analyzes the variation of facial activity with pain stimulus intensity and among subjects [5]. We propose two distinct methods to assess facial expressiveness and apply them on the BioVid Heat Pain Database [2, 5]. Experimental results show that facial response is rare during low intensity pain stimulation and that the proposed measures can successfully identify highly expressive individuals, for whom pain stimuli can be classified reliably, and non-expressive individuals, who may have felt less pain than intended and encoded in labels.
How much does it hurt? Accurate assessment of pain is very important for selecting the right treatment, however current methods are not sufficiently valid and reliable in many cases. Automatic pain monitoring may help by providing an objective and continuous assessment. In this paper [6] we propose an automatic pain recognition system combining information from video and biomedical signals, namely facial expression, head movement, galvanic skin response, electromyography and electrocardiogram. Using the BioVid Heat Pain Database [2, 5], the system is evaluated in the task of pain detection showing significant improvement over the current state of the art. Further, we discuss the relevance of the modalities and compare person-specific and generic classification models.
In this work, we present methods for the personalization of a system for the continuous estimation of pain intensity from bio-physiological channels [8]. 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 standard method for prediction of the absence and presence of pain has long been self-report. However, for patients with major cognitive or communicative impairments, it would be better if clinicians could quantify pain without having to rely on the patient's self-description. Here, we present [9] a newly pain intensity measurement method based on multiple physiological signals, including blood volume pulse (BVP), electrocardiogram (ECG) [2, 5, 16], and skin conductance level (SCL), all of which are induced by external electrical stimulation. The proposed pain prediction system consists of signal acquisition and preprocessing, feature extraction, feature selection and feature reduction, and three types of pattern classifiers. Feature extraction phase is devised to extract pain-related characteristics from short-segment signals. A hybrid procedure of genetic algorithm-based feature selection and principal component analysis-based feature reduction was established to obtain high-quality features combination with significant discriminatory information. Three types of classification algorithms—linear discriminant analysis, k-nearest neighbor algorithm, and support vector machine—are adopted during various scenarios, including multi-signal scenario, multi-subject and between-subject scenario, and multi-day scenario. The classifiers gave correct classification ratios much higher than chance probability, with the overall average accuracy of 75% above for four pain intensity. Our experimental results demonstrate that the proposed method can provide an objective and quantitative evaluation of pain intensity. The method might be used to develop a wearable device that is suitable for daily use in clinical settings.

III. Materials and Methods

The proposed system represents a significant advancement in pain recognition by seamlessly integrating feature extraction and classification through a deep learning approach [3, 19, 21, 33]. Unlike conventional methods relying on manual extraction by medical experts, this system automates the process, enhancing efficiency and adaptability. Leveraging multi-level context information, it achieves superior accuracy in pain recognition, demonstrating the effectiveness of deep learning in healthcare applications. Competitive performance with prior approaches underscores its potential, aiming to reduce dependence on medical expertise for feature extraction from physiological signals. This not only marks a substantial leap in automatic pain recognition systems but also highlights the system's potential impact on improving healthcare practices through more accessible and accurate assessments. It also included a "Stacking Classifier" and a hybrid model "CNN+BILSTM+GRU" are introduced to enhance pain recognition, achieving an impressive 99% accuracy with the stacking classifier. The stacking classifier, known for its ensemble capabilities, contributes to robust predictions. The hybrid model, incorporating convolutional and recurrent neural networks, leverages multi-level context information for improved accuracy. The user-friendly Flask framework with SQLite integration enhances practical usability, providing a seamless experience for user testing in machine learning applications focused on pain recognition with physiological signals.

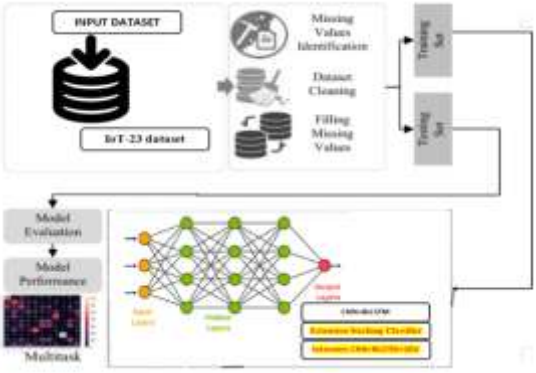


Fig.1 Proposed Architecture

The project begins with an input dataset comprising physiological signals for pain recognition. The dataset undergoes meticulous preprocessing to enhance its quality and relevance. Following this, the data is split into training and testing sets. The core of the system involves building models, including a "Stacking Classifier" as an extension and a sophisticated hybrid model, "CNN+BiLSTM+GRU." The Stacking Classifier enhances the predictive capabilities, achieving 99% accuracy in pain recognition. The hybrid model, leveraging Convolutional Neural Network (CNN) [30] with Bidirectional Long Short-Term Memory (BiLSTM) and Gated Recurrent Unit (GRU), captures multi-level context information for improved pattern recognition. Evaluation metrics assess the model's performance, ensuring its effectiveness in accurately

identifying pain based on physiological signals. This comprehensive system architecture combines ensemble learning and advanced neural network techniques for enhanced pain recognition.

A) Dataset Collection:

Here, the dataset is examined to understand its structure, contents, and features. This exploration may involve checking data types, dimensions, statistical summaries, and visualizations to gain insights into the data. BioVid Heat Pain Database [2] is a multi-modal dataset including visual and physiological signals. The healthy subjects are thermally stimulated to induce pain under controlled temperature conditions. Pain thresholds are divided into five classes: Pain 0, Pain 1, Pain 2, Pain 3, and Pain 4. Pain 0 is the baseline class that represents the non-painful class.

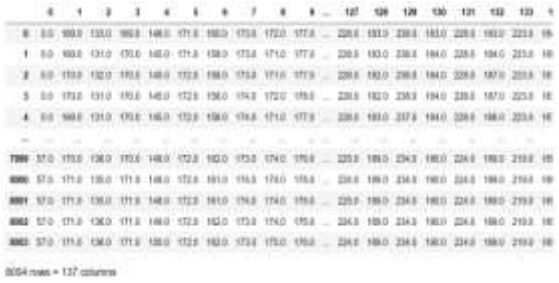


Fig.2 Dataset Collection

B) Processing:

Data processing involves transforming raw data into valuable information for businesses. Generally, data scientists process data, which includes collecting, organizing, cleaning, verifying, analyzing, and converting it into readable formats such as graphs or documents. Data processing can be done using three methods i.e., manual, mechanical, and electronic. The aim is to increase the value of information and facilitate decision-making. This enables businesses to improve their operations and make timely strategic decisions. Automated data processing solutions, such as computer software programming, play a significant role in this. It can help turn large amounts of data, including big data, into meaningful insights for quality management and decision-making.

Feature selection: Feature selection is the process of isolating the most consistent, non-redundant, and relevant features to use in model construction. Methodically reducing the size of datasets is important as the size and variety of datasets continue to grow. The main goal of feature selection is to improve the performance of a predictive model and reduce the computational cost of modeling.

Feature selection [30], one of the main components of feature engineering, is the process of selecting the most important features to input in machine learning algorithms. Feature selection techniques are employed to reduce the number of input variables by eliminating redundant or irrelevant features and narrowing down the set of features to those most relevant to the machine learning model. The main benefits of performing feature selection in advance, rather than letting the machine learning model figure out which features are most important.

C) Algorithms:

Random Forest: Random Forest is an ensemble learning algorithm that builds a multitude of decision trees during training. For each tree, a random subset of features is considered at each split, adding an element of randomness. In the context of "Pain Recognition With Physiological Signals Using Multi-Level Context Information," Random Forest could be used for classification tasks based on physiological signals. Its ensemble nature often provides robust performance and can handle complex relationships within the data [7, 32].

CNN + BILSTM: This combination involves a Convolutional Neural Network (CNN) followed by a Bidirectional Long Short-Term Memory (BILSTM) network. CNNs are adept at capturing spatial patterns, while BILSTMs excel in capturing sequential dependencies. In the project, this combination might be used for extracting features from physiological signal data, considering both spatial and temporal aspects for improved context awareness in pain recognition [30].

There is a simple formula to do so:

Dimension of image = (n, n)

Dimension of filter = (f,f)

Dimension of output will be ((n-f+1) , (n-f+1)) (1)

You should have a good understanding of how a convolutional layer works at this point. Let us move to the next part of the CNN architecture.

CNN + BILSTM + GRU: This combination extends the previous one by adding a Gated Recurrent Unit (GRU) to the architecture. GRUs are similar to LSTMs (Long Short-Term Memory networks) and are effective in capturing long-range dependencies in sequential data. In the project, this combination likely enhances the model's ability to capture intricate patterns in physiological signals, especially when considering multi-level context information [30].

Stacking Classifier: Stacking is an ensemble learning technique that combines multiple base classifiers to improve predictive performance. In a Stacking Classifier, the predictions of multiple classifiers are used as input features for a meta-classifier. This meta-classifier then makes the final prediction. In the context of the project, a Stacking Classifier might combine the predictions of models trained with Random Forest, CNN + BILSTM, and CNN + BILSTM + GRU to achieve a more robust and accurate pain recognition system, leveraging the strengths of each individual model.

Let {X,Y}{X,Y} denoted the data set (sample, label), θ the parameters.

A classification algorithm is a decision function f(x;θ)f(x;θ) together with a cost/risk function C(f(·;θ),X,Y)C(f(·;θ),X,Y). (2)

Specifying the functional form of ff and CC completely specifies the classification algorithm. θ^=argminθC(θ)θ^=argminθC(θ) defines the classifier.

IV. Results And Discussion

Accuracy: A test's accuracy is its capacity to distinguish patient from healthy cases. To measure test accuracy, calculate the fraction of true positive and true negative in all evaluated cases. Mathematically, this is:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} (3)$$

Precision: Precision measures the percentage of positive cases or samples accurately classified. Precision is calculated using the formula:

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} (4)$$

Recall: Machine learning recall evaluates a model's capacity to recognise all relevant instances of a class. It shows a model's completeness in capturing instances of a class by comparing accurately predicted positive observations to total positives.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} (5)$$

F1-Score: Machine learning model accuracy is measured by F1 score. Combining model precision and recall scores. The accuracy statistic measures how often a model predicted correctly throughout the dataset.

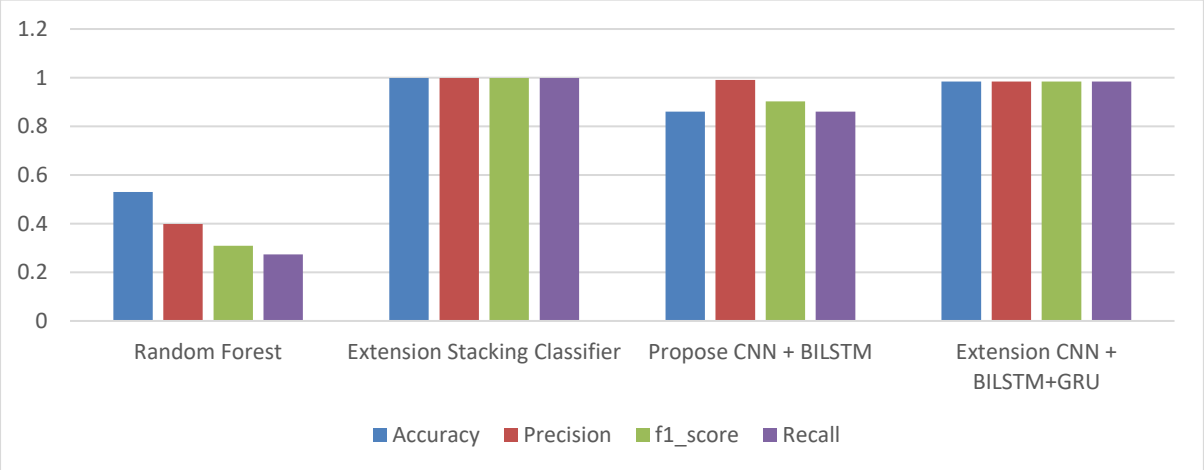
$$\text{F1 Score} = 2 * \frac{\text{Recall X Precision}}{\text{Recall} + \text{Precision}} * 100 (6)$$

Table (1) evaluate the performance metrics—Accuracy, precision, recall and F1-score —for each algorithm. The Extension CNN + BILSTM+GRU consistently outperforms compared to all other algorithms. The tables also offer a comparative analysis of the metrics for the other algorithms

Table.1 Performance Evaluation Table

ML Model	Accuracy	Precision	f1_score	Recall
Random Forest	0.530	0.398	0.309	0.274
Extension Stacking Classifier	0.999	0.999	0.999	0.998
Propose CNN + BILSTM	0.861	0.991	0.903	0.861
Extension CNN + BILSTM+GRU	0.984	0.984	0.984	0.984

Graph.1 Comparison Graphs



Accuracy is represented in blue, precision in red, recall in purple and F1 - Score in green Graph (1). In comparison to the other models, the Extension CNN + BILSTM+GRU shows superior performance across all metrics, achieving the highest values. The graphs above visually illustrate these findings.

V. CONCLUSION

Deep learning models, such as neural networks, possess the capability to automatically learn and extract complex patterns directly from raw data. In this case, using physiological signals, the deep learning approach bypasses the necessity of manual feature extraction. Instead, it autonomously discerns relevant features from the signals, which are then utilized for pain classification. This streamlines the process and reduces reliance on domain-specific expertise for feature extraction. Physiological signals contain information at various levels or scales. Leveraging multi-level context information involves analyzing these signals at different depths or perspectives. This multilevel understanding allows for a more comprehensive analysis, capturing intricate patterns and nuanced variations present within the signals. As a result, the model's ability to distinguish between different pain levels or pain states improves significantly compared to approaches that only consider single-level information. Integrating multiple physiological signals, each capturing different aspects of the body's response to pain, leads to a more comprehensive and holistic representation of the pain experience. EDA measures changes in skin conductance, while ECG monitors heart activity. Combining these signals provides a more detailed and diverse set of information for the model to learn from, resulting in improved accuracy and robustness in pain recognition. Deep learning methods, with their ability to automatically extract hierarchical representations from data, showcase superior performance compared to traditional methods in various domains, including pain recognition. By leveraging the inherent complexities within physiological signals, deep learning models can capture intricate patterns that might be missed by conventional feature extraction methods. Consequently, the deep learning approach demonstrates better accuracy, sensitivity, and overall performance in pain recognition tasks involving physiological signals.

The project can delve deeper into exploring and improving latent sequence information within physiological signals. By enhancing the context information extracted from these signals, the system can potentially achieve more nuanced and accurate pain recognition. This involves investigating advanced techniques to reveal subtle patterns and dependencies within the sequences. To further enhance the analysis of physiological signals, the project can explore the development of more advanced architectures, both spatial and temporal. This entails experimenting with sophisticated neural network structures that can better capture and interpret the complex spatial and temporal characteristics inherent in physiological data, thereby improving overall performance. The proposed method can be applied to diverse datasets beyond the initial one. By comparing its performance with existing pain recognition methods, the project can assess the generalizability and effectiveness of the proposed approach. This step is crucial for understanding the system's robustness and potential applicability across various healthcare scenarios. Investigating the integration of additional physiological signals, such as electromyography (EMG) and electrocardiography (ECG), can contribute to enhancing the accuracy and robustness of pain recognition. This broader set of signals may provide richer information, offering a more comprehensive understanding of a patient's physiological state during pain-related tasks. The exploration of hidden information within physiological signal sequences can extend beyond pain recognition to other healthcare applications. This may include applications such as emotion recognition or stress detection, broadening the impact of the project and contributing to advancements in various healthcare domains. The project can consider incorporating real-time monitoring and feedback systems. This would enable immediate pain recognition and intervention in healthcare settings, providing timely information for healthcare professionals to deliver prompt and personalized care based on the continuous analysis of physiological signals.

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