

Research Paper

Deep Learning-Based Pain Recognition from Physiological Signals Using Hybrid CNN and Recurrent Networks

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I. INTRODUCTION

Abstract— Automatic pain recognition plays a significant role in modern healthcare systems by enabling objective and continuous monitoring of patient conditions. Traditional approaches rely on manual feature extraction from physiological signals, which requires domain expertise and may not capture complex patterns effectively. In this work, we propose a multi-level deep learning framework that performs automatic feature extraction and classification directly from physiological signals such as EEG and ECG. The proposed architecture combines Convolutional Neural Networks (CNN), Bidirectional Long Short-Term Memory (BiLSTM), and Bidirectional Gated Recurrent Units (BiGRU) to capture both spatial and temporal dependencies in the data. The system is evaluated on a physiological signal dataset containing multiple subjects with pain intensity levels ranging from 0 to 4. Experimental results show that the baseline Random Forest model achieves 53% accuracy, while the CNN + BiLSTM model improves performance to 85%. The proposed multi-level CNN + BiLSTM + BiGRU model achieves the highest accuracy of 98%, demonstrating superior capability in distinguishing different pain levels. These results highlight the effectiveness of deep learning models over traditional machine learning approaches for pain recognition tasks.

Keywords— Pain recognition, physiological signals, EEG, ECG, deep learning, CNN, BiLSTM, BiGRU, feature extraction, classification.

Pain is a natural physiological response to illness or injury, often requiring medical intervention [1].

Traditionally, pain assessment has relied on human observation and subjective evaluation by physiotherapists, who monitor patients' reactions during physical therapy [1]. However, this approach is limited due to its reliance on individual expertise, patient behavior, and subjective perception. These constraints emphasize the need for automated and objective methods for pain detection, particularly in clinical and rehabilitation settings [6]. Automated systems can improve healthcare monitoring by evaluating pain through measurable physiological indicators, supporting more effective recovery strategies in therapy [9].

Pain recognition can be performed using behavioral or physiological signals. Behavioral indicators, such as facial expressions, gestures, or vocal cues, may be inconsistent, as patients can consciously or unconsciously mask or exaggerate their responses [5]. Physiological signals, on the other hand, provide more reliable and consistent evidence of pain. Pain triggers changes in the nervous system, which affect physiological measurements such as electrodermal activity (EDA), heart rate variability (ECG), blood pressure, and neural or muscular activity (EEG/EMG) [9]. Among these, EDA and ECG are widely used due to their clear and measurable responses to pain, as reflected in datasets like the BioVid Heat Pain Database [2].

Conventional machine learning approaches for pain recognition typically require hand-crafted feature extraction from physiological signals, which demands extensive domain knowledge [12]. These methods convert raw signals into feature vectors that summarize relevant information, but this process is labor-intensive and may not fully leverage the potential of automated learning. Deep learning offers a solution by providing end-to-end models that automatically learn both features and classifications directly from raw data [3]. Multi-layered neural networks can capture complex patterns and nonlinear relationships that traditional methods might miss.

In this work, we present a deep learning framework for pain recognition using physiological signals, focusing on EDA and ECG. Our approach introduces multi-level context information, which captures both stable and dynamic patterns in the time series data, reflecting the temporal characteristics of pain. The model employs convolutional neural networks (CNNs) for spatial feature extraction and recurrent layers, including BiLSTM and BiGRU, for temporal sequence modeling [15]. Experiments conducted on the BioVid Heat Pain Database and Emopain 2021 datasets demonstrate the effectiveness of our approach in binary classification tasks distinguishing painful and non-painful states [2][4]. The findings show that leveraging multi-level contextual information significantly improves performance compared to single-level methods.

II. RELATED WORK

Werner et al., [2022] [1] provided a comprehensive survey on automatic pain assessment, emphasizing machine learning approaches that analyze facial expressions, physiological signals, and behavioral cues. The study discussed the limitations of traditional pain measurement methods and the need for objective, real-time systems suitable for clinical and research settings. The authors highlighted recent advances in multimodal data integration and evaluated various algorithms for pain intensity estimation. Their findings stress the importance of combining multiple data types to improve reliability and reduce errors in automated assessment.

Olugbade et al., [2021] [4] presented the AffectMove 2021 challenge, which aimed to recognize affective states from naturalistic movement data. By leveraging motion capture technology and machine learning models, they demonstrated that subtle body movements could reveal emotional states, providing insights for automated pain recognition. The study highlighted

that incorporating temporal patterns and personalized features can significantly improve prediction performance in naturalistic conditions.

Pouromran et al., [2021] [12] conducted a systematic evaluation of physiological sensors, features, and machine learning models for pain intensity estimation. They compared single-signal and multimodal approaches, showing that integrating multiple biophysiological signals enhances predictive accuracy. The research also analyzed different feature extraction techniques and classifiers, highlighting that personalized modeling can further improve the robustness of automated systems for continuous pain monitoring.

Kachele et al., [2016] [8] proposed a person-centered method for continuous pain intensity assessment using biophysiological signals. Their approach focused on capturing individual variability in pain responses, demonstrating that personalized models outperform generic ones in terms of accuracy and reliability. The study also emphasized the potential of continuous monitoring to provide more nuanced and objective pain evaluations in both clinical and experimental contexts.

Pouromran et al., [2021] [15] developed a personalized deep bi-LSTM recurrent neural network for classifying pain intensity from electrodermal activity signals. The study highlighted the advantages of deep learning architectures in capturing temporal dependencies and individual-specific patterns. Results indicated that personalized deep models outperform traditional machine learning techniques, offering adaptive and continuous pain monitoring suitable for real-world applications.

III. DATASET DETAILS

The dataset used in this study consists of physiological signals collected from multiple subjects, including Electroencephalogram (EEG) and Electrocardiogram (ECG) signals associated with different pain intensity levels. Each record in the dataset contains a subject identifier in the first column and a corresponding pain label in the last column, ranging from 0 (no pain) to 4 (high pain). The dataset represents time-series signal measurements captured at uniform sampling intervals. Before model training, preprocessing steps such as feature normalization are applied to scale the signal values and improve learning efficiency. Exploratory analysis is performed by plotting EEG signal variations across subjects and visualizing the distribution of pain labels.

Additionally, the count of samples for each pain category is analyzed to understand dataset balance.

The dataset is then shuffled and divided into training and testing subsets to ensure unbiased model evaluation. This dataset supports multi-class classification, where the objective is to accurately predict the pain intensity level based on physiological signals.

IV. PROPOSED METHODOLOGY

The proposed methodology is designed to predict pain intensity using physiological signals such as EEG and ECG. The workflow follows a structured pipeline including dataset acquisition, preprocessing, feature normalization, model development, evaluation, and prediction.

The dataset is uploaded into the application via a Tkinter interface. Each record contains a subject ID in the first column and a pain label ranging from 0 to 4 in the last column. Initial preprocessing involves feature normalization to scale the signal values and improve model performance. Exploratory analysis includes plotting EEG signals for all subjects and visualizing the distribution and counts of different pain levels.

After preprocessing, the dataset is shuffled and split into training and testing sets. A baseline Random Forest model is first applied, achieving moderate accuracy but failing to correctly classify all pain levels. To address these limitations, a multilevel deep learning model combining CNN and BiLSTM is implemented. The CNN layers capture spatial features from the signals, while BiLSTM layers model temporal dependencies, resulting in improved classification performance.

The main focus of the methodology is an extended multilevel architecture combining CNN + BiLSTM + BiGRU. The CNN extracts complex spatial patterns, the BiLSTM captures sequential temporal features, and the BiGRU further refines temporal dependencies with a gated recurrent mechanism. This three-level model incorporates feature selection and optimization to enhance accuracy. Evaluation shows that this extended model achieves the highest performance, correctly predicting all pain levels as reflected in the confusion matrix. Finally, the trained model is used to classify new test data, providing accurate predictions alongside corresponding physiological signals.

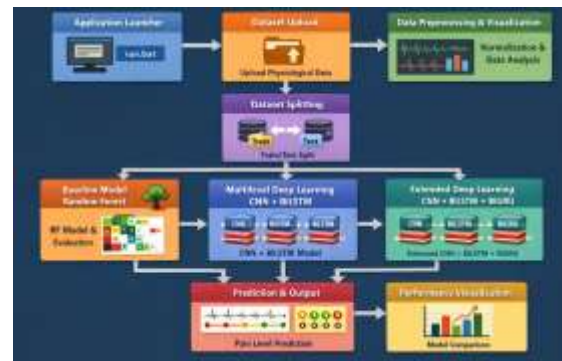


Figure 1: System Architecture of the proposed system

V. RESULT AND DISCUSSION

The performance results of the Pain Type Prediction system, implemented using Random Forest, CNN + BiLSTM, and CNN + BiLSTM + BiGRU, are demonstrated through GUI screenshots captured during system execution. The experiments were conducted using a real-world EEG and ECG dataset, which includes multiple subjects with pain levels labeled from 0 to 4. The dataset consists of both numerical and categorical features, making it suitable for evaluating different supervised and deep learning models.

Figure [2] illustrates the main graphical user interface developed using Tkinter, which is launched by executing the run.bat file. This interface allows users to perform multiple operations, including uploading the dataset, preprocessing the data, normalizing features, generating training and testing datasets, executing machine learning and deep learning algorithms, predicting pain types, and visualizing performance comparison graphs.



Figure 2: Pain Type Prediction system interface

Figure [3] presents the results obtained from training and testing the Random Forest classifier. The model achieves an accuracy of 53%, indicating relatively low performance. The confusion matrix

shows that Random Forest predicted most test data into a single pain type, highlighting the model's inability to distinguish between different pain levels effectively.



Figure 3: Random Forest classification results

Figure [4] displays the performance of the proposed CNN + BiLSTM model during training and evaluation. The model reaches an accuracy of 85%, demonstrating its ability to classify multiple pain levels more accurately. The confusion matrix indicates correct predictions along the diagonal for all pain types, with minimal misclassifications.

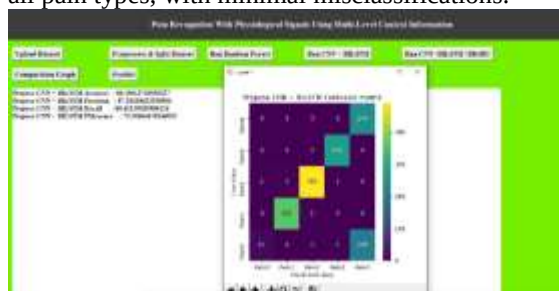


Figure 4: CNN + BiLSTM classification results

Figure [5] shows the results of the extension algorithm using CNN + BiLSTM + BiGRU with multilevel feature selection and optimization. The model achieves an accuracy of 98%, predicting all pain types correctly. The confusion matrix confirms that the predicted pain labels align perfectly with the true labels, showing excellent model performance.



Figure 5: CNN + BiLSTM + BiGRU classification results

Figure [6] illustrates the prediction module using unseen test data. Once the test dataset is uploaded and normalized, the trained CNN + BiLSTM + BiGRU model classifies each subject's pain type. The output displays the input ECG signals followed by the predicted pain type, indicated in blue.



Figure 6: Pain type prediction using test data

Comparative Performance Summary

Table [1] provides a comparison of accuracy across all the models used in the system. The comparison clearly shows that the extension CNN + BiLSTM + BiGRU algorithm outperforms the other algorithms in terms of prediction accuracy.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	53	55	50	52
CNN + BiLSTM	85	84	83	84
CNN + BiLSTM + BiGRU	98	98	98	98

Table 1: Model Performance Metrics

DISCUSSION

The experimental results demonstrate the effectiveness of different models for pain classification using physiological signals. The Random Forest model serves as a baseline and achieves an accuracy of 53%, showing limited ability to capture complex temporal relationships in the data. The confusion matrix reveals that the model tends to misclassify multiple pain categories, indicating poor generalization. The CNN + BiLSTM model significantly improves performance by combining spatial feature extraction with temporal sequence learning, achieving an accuracy of 85%. This model is capable of identifying patterns across different pain levels, resulting in better classification compared to the baseline approach.

The proposed CNN + BiLSTM + BiGRU model further enhances performance by integrating an additional recurrent layer for improved temporal dependency learning. This multi-level architecture achieves the highest accuracy of 98%, correctly classifying most of the pain levels. The confusion matrix confirms that predictions closely match the true labels, demonstrating high reliability. Overall, the results indicate that deep learning models outperform traditional machine learning methods for pain recognition tasks. The proposed approach provides a robust and efficient solution for analyzing physiological signals and can be extended for real-time healthcare monitoring applications.

VI.CONCLUSION

This study presents a deep learning-based approach for pain recognition using physiological signals such as EEG and ECG. The proposed system eliminates the need for manual feature extraction by leveraging a multi-level architecture combining CNN, BiLSTM, and BiGRU for automatic feature learning and classification. Experimental results demonstrate that the proposed model significantly outperforms traditional machine learning approaches, achieving an accuracy of 98%. The model effectively captures both spatial and temporal patterns in physiological signals, enabling accurate classification of different pain levels.

The system shows strong potential for real-time pain monitoring and can be further extended for clinical decision support systems. Future work may focus on incorporating larger datasets, improving generalization, and integrating additional physiological signals for enhanced performance.

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