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RESEARCH ARTICLE

Pain Recognition With Physiological Signals Using Multi-Level Context Information

KIM NGAN PHAN, NGUMIMI KAREN IYORTSUUN, SUDARSHAN PANT, HYUNG-JEONG YANG, (Member, IEEE), AND SOO-HYUNG KIM, (Member, IEEE)
Department of Artificial Intelligence Convergence, Chonnam National University, Gwangju 61186, South Korea

Corresponding author: Soo-Hyung Kim (shkim@jnu.ac.kr)

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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 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 uni-level context information based on Part A of the BioVid Heat Pain database and the Emopain 2021 dataset. For Part A of the BioVid 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.

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 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 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 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). Skin

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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.

The task of automatic pain 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 [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 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 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 BioVid Heat Pain Database [2] and the Emopain 2021 dataset [4]. Our method uses simple preprocessed physiological signals that are available in the datasets.

Part A of the BioVid 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 Figure 7, 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. The architecture is depicted in Figure 1.

For Part A of the BioVid Heat Pain database, the authors in [5] propose a subject subset that excludes 20 study participants who did not respond visibly to the pain stimuli. In this work, we use 67 subjects in [5] recommendations out of 87 subjects. Simultaneously, we also compare previous studies based on 87 subjects.

To demonstrate the performance of multi-level context information for pain recognition, we also perform the experiment based on the physiological signals of the Emopain 2021 dataset. The main contributions of this paper are as follows:

- We propose a deep learning approach based on physiological signals for pain recognition. Our method does not perform additional signal preprocessing, but directly uses the simple preprocessed physiological signals available in the dataset. Our method has the role of feature extraction and classification, completely replacing manual extraction methods that require highly specialized knowledge.
- Our experimental results prove that multi-level context information is more significant than uni-level context information based on Part A of the BioVid Heat Pain database and the Emopain 2021 dataset.
- The multi-level context information which is explored from hidden sequence information gives the competitive performance of classification tasks based on Part A of the BioVid Heat Pain database.

This paper includes the following sections. Section II represents the background knowledge in deep learning employed for pain recognition automation architecture. Section III consists of the sub-net architectures used in our architecture and the analysis of the multi-level context information. Section IV reports the dataset, training details, illustrations, comparative results of the proposed model, and discussion. Section V is the conclusion of the paper.

II. RELATED WORKS

For machine learning, there are many effective methods used in pain recognition. In [6], the authors explore both video and

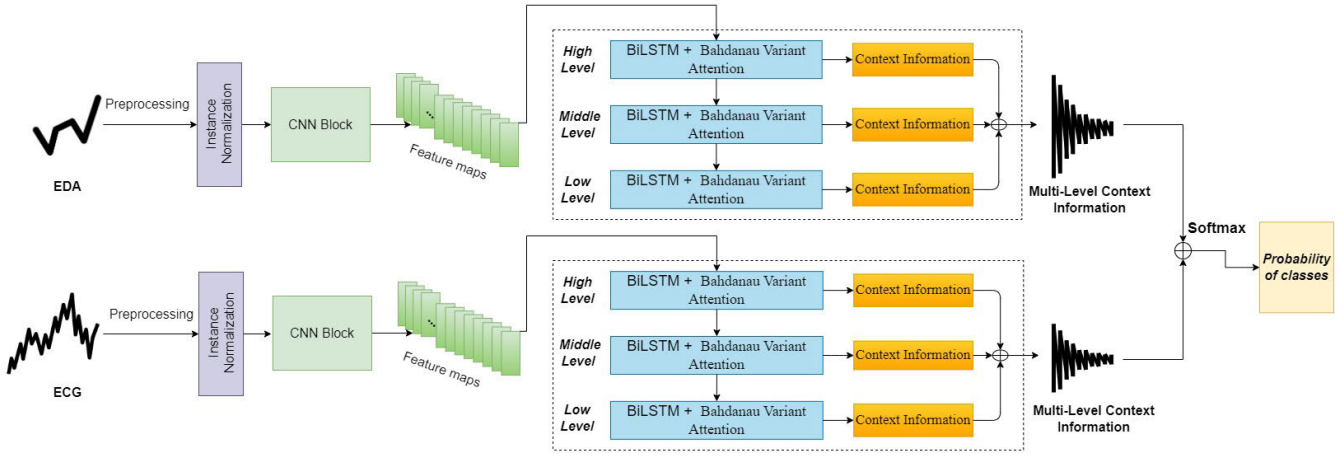


FIGURE 1. Overview of the proposed model.

physiological data, they manually propose features extracted from each signal channel (EMG, ECG, EDA) for pain perception, and their results indicate the Random Forest (RF) model [7] is effective for automatic pain recognition. Similarly, the authors in [8] perform a broad spectrum of different feature extraction algorithms to extract robust information from EMG, ECG and EDA signals for the RF classifier. In [9], the authors perform complex signal preprocessing for BVP, ECG and EDA. They then extract statistical features for each of the signal channel. Feature selection and principal component analysis are performed to select high-quality features from the statistical features. Then they use simple models including Linear Discriminant Analysis (LDA) [10], k-Nearest Neighbor (kNN) algorithm, and Support Vector Machine (SVM) [11] for classification. In [12], the authors extract features from EDA, ECG, and EMG signals and explore different machine learning models which contain Linear Regression, Support Vector Regression (SVR) [13], Neural Networks, and Extreme Gradient Boosting Regression (XGBoost) [14]. Their results indicate that the EDA signal significantly affects pain intensity estimation. In [15], the authors perform bidirectional LSTM to extract representative features from the EDA signal. This representative feature is used as the input of the XGBoost for pain intensity classification.

There are many methods to apply the extracted features from physiological signals for deep learning models. In [16], the authors employ the hand-crafted features extracted from EDA and ECG signals based on [6]. They then implement multi-task learning with neural networks (MT-NN) approach to compare logistic regression (LR), and SVM. Their results show that MT-NN outperforms any other algorithms for pain recognition. In [17], the authors extract the hand-crafted features from the deconvolved skin conductance data and heart rate variability. The experiments on machine learning and recurrent neural network regression are explored for pain recognition. Their results show the ability to capture temporal dependencies of LSTM. In [18], the Butterworth filter is applied to remove noise and artifacts. The authors extract EDA, ECG, EMG handcrafted features, and RNN-generated features. They then select 50 features for the Artificial Neural Network (ANN) input. The proposed method outperforms most of the previous research for pain recognition.

In addition, several methods fully apply deep learning for both feature extraction and classification model. In [19], the authors employ a Butterworth filter to remove noise from ECG and EDA signals. Based on these modalities, their results indicate the effectiveness of the combination of convolutional and LSTM networks for pain assessment. In [20], the authors process EDA, ECG, and EMG physiological signals with a Butterworth filter and data augmentation to enhance samples. Their study mainly builds inference models based on convolutional neural networks. Their experimental evaluations demonstrate that the proposed uni-modal architecture using EDA and the deep fusion approaches significantly outperform previous methods. In [21], the authors propose a multi-modal Deep Denoising Convolutional AutoEncoders (DDCAE) architecture using Convolutional Neural Networks. They reduce the sampling rate, noise, and artifacts from EDA, ECG, and EMG signals and perform data augmentation. In DDCAE, the authors propose a gating layer to create a weighted representation based on the channel-specific latent representations for each input channel. The weighted representation is then used to optimize an inference model for classification or the regression task. The attention mechanism is also applied for weighted representation to improve performance.

III. PROPOSED METHOD

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 recognition. Firstly, we recommend architectures suitable for physiological signals including spatial and temporal architectures.

Secondly, we present Bahdanau Variant Attention to extract context information. In the last section, we introduce the multi-level context information in detail.

A. SPATIAL ARCHITECTURE

Inspired by previous studies on the breakthrough performance of deep learning networks, the proposed architecture 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 handcrafted 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 classification tasks. The pooling layers reduce the number of parameters 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. We opt a non-linear activation function named Exponential Linear Unit (ELU) instead of ReLU to retain negative values. The Exponential Linear Unit (ELU) activation 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 channel. Finally, the feature maps are averagely pooled to reduce the spatial resolution. A simple spatial architecture designed for physiological signals is built, as shown in Figure 2.

B. 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 some errors in backpropagation 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 information available to the network. Therefore, BiLSTMs help extract temporal information and capture context information as a time series of physiological signals. It is illustrated in Figure 3.

C. 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 translation 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 attention 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 annotations helps context vectors carry more selective context information than hidden states.

Inspired by the Bahdanau attention mechanism, we propose 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. The context vector of the variant is calculated as follows:

$$c = c^{(forward)} \oplus c^{(backward)} \tag{1}$$

For the input sequence with length T, the annotation h_t $(t = 1, ..T)$ is a concatenation of forward hidden states $\overrightarrow{h_t}$ and backward one $\overleftarrow{h_t}$. At the time t, the annotation $h_t = [\overrightarrow{h_t}, \overleftarrow{h_t}]$ summarizes the information of forward and backward in the input sequence. The context vector $c^{(forward)}$ is calculated similarly to Bahdanau [22]:

$$c^{(forward)} = \sum_{t=1}^{T} \alpha_t^{(forward)} h_t \tag{2}$$

where

$$\alpha_t^{(forward)} = softmax(e_t^{(forward)}) \tag{3}$$

$$e_t^{(forward)} = v_a^T tanh(W_a l_t^{(forward)} + U_a h_t) \tag{4}$$

where W_a, U_a, v_a are weight matrices with the alignment model a as a feedforward neural network. We let $l_t^{(forward)}$ be the scaled last forward hidden state at the time t. The last hidden state contains all the temporal information from the hidden representations and inputs of the previous time step. The $c^{(backward)}$ is implemented similarly to the $c^{(forward)}$. In addition, the combination of the scaled last hidden information is given as follows:

$$l = l^{(forward)} \oplus l^{(backward)} \tag{5}$$

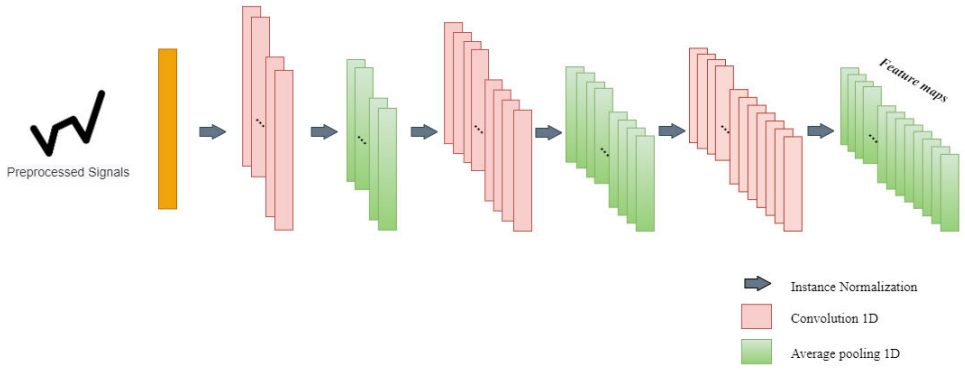


FIGURE 2. CNN spatial architecture.

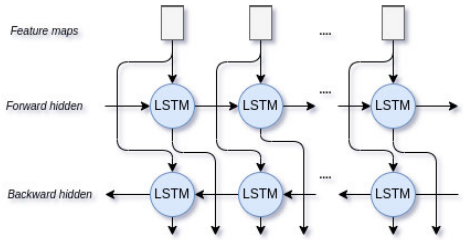


FIGURE 3. BiLSTMs architecture.

D. MULTI-LEVEL CONTEXT INFORMATION

This section introduces a method capable of extracting multi-level representations from context information. We first perform 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. Concurrently, 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 information 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. We implement 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.

In each level block, the hidden information and the scaled last hidden information are fed into Bahdanau Variant Attention to extract the context vector. Combining the scaled last hidden information and the context vector creates context information. Finally, we combine the context information of all level blocks generating multi-level context information, as shown in Figure 6. Let k be the level of the block, the context information CI and multi-level context information $MLCI$ are expressed in the following formula:

$$CI^k = c^k \oplus l^k \tag{6}$$

$$MLCI = CI^1 \oplus CI^2 \oplus \ldots \oplus CI^m \tag{7}$$

We perform $m = 3$ for the network architecture corresponding to 3 levels: High Level, Middle Level, and Low Level. In this work, we combine multi-level context information from EDA and ECG physiological signals. The representations for the classification tasks are shown in Figure 7. The detail of the last column c) is described in Figure 8. We choose the classification of Pain 0 and Pain 4 to explain the composition of the illustration. The combined representation is dropped out to avoid overfitting. Finally, the fully connected layer (FC) is passed to compress the feature dimension and Softmax function is applied to predict the probability of pain occurrence. An overview of the architecture is illustrated in Figure 1.

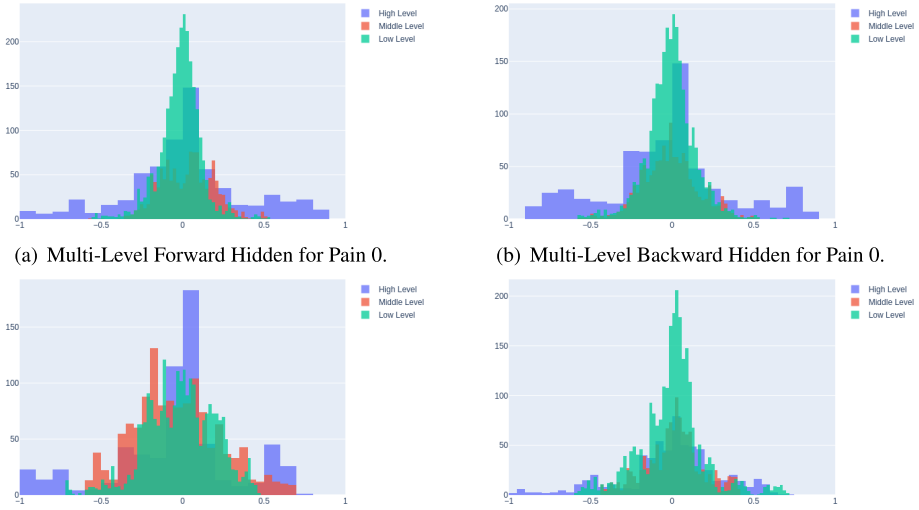
E. IMPLEMENTATION DETAILS

This network is trained with python programming language using Keras on Tensorflow version 2.7. Adam optimization [23] is performed to optimize the binary cross-entropy loss function. In binary classification, the cross-entropy loss function is defined as:

$$\mathcal{L} = -(y \log(p) + (1 - y) \log(1 - p)) \tag{8}$$

where y is the class with the binary value (0 or 1) and p is the prediction probability of the class.

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. The training process pauses when the validation loss results are



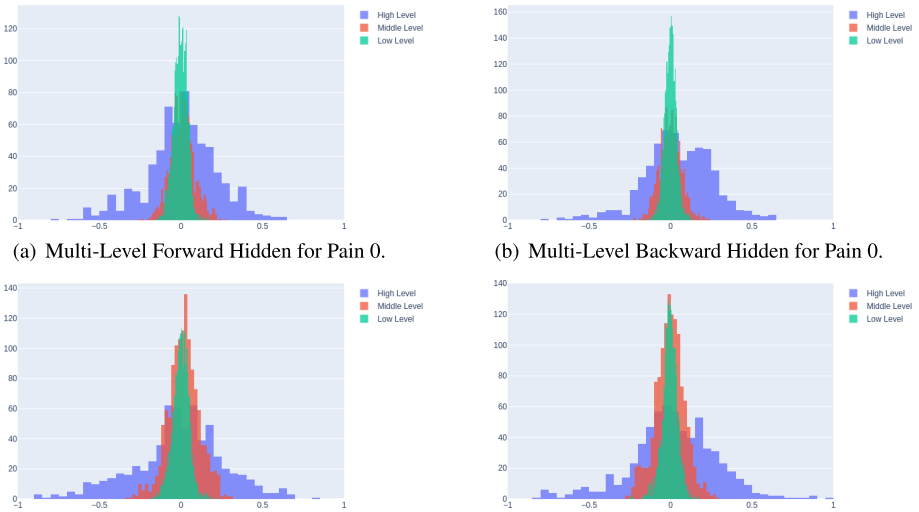
(a) Multi-Level Forward Hidden for Pain 0.

(b) Multi-Level Backward Hidden for Pain 0.

(c) Multi-Level Forward Hidden for Pain 4.

(d) Multi-Level Backward Hidden for Pain 4.

FIGURE 4. Multi-level hidden information from EDA signal for the classification pain 0 and pain 4 of subject 071614-m-20. The training process performs LOSO cross-validation evaluation with 67 subjects. They are histogram charts with the x-axis representing the value and the y-axis representing the frequency of the hidden information. The blue, red, and green colors represent high level, Middle Level, and Low Level, respectively.



(a) Multi-Level Forward Hidden for Pain 0.

(b) Multi-Level Backward Hidden for Pain 0.

(c) Multi-Level Forward Hidden for Pain 4.

(d) Multi-Level Backward Hidden for Pain 4.

FIGURE 5. Multi-level hidden information from ECG signal for the classification pain 0 and pain 4 of subject 071614-m-20. The training process performs LOSO cross-validation evaluation with 67 subjects. They are histogram charts with the x-axis representing the value and the y-axis representing the frequency of the hidden information. The blue, red, and green colors represent high level, Middle Level, and Low Level, respectively.

not improved after five executions. The parameters for the proposed model are given in Table 1.

For the EmoPain 2021 dataset, we use 3-fold cross-validation on the training set. We then employ the average of 3-fold prediction probability to give the final prediction probability on the validation and the test sets. The evaluation employs the F1 score of each class, MCC, and accuracy (in %) for performance comparison. The parameters are also given in Table 2.

IV. EXPERIMENTAL RESULTS

A. DATASET

1) BioVid HEAT PAIN DATABASE

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. The

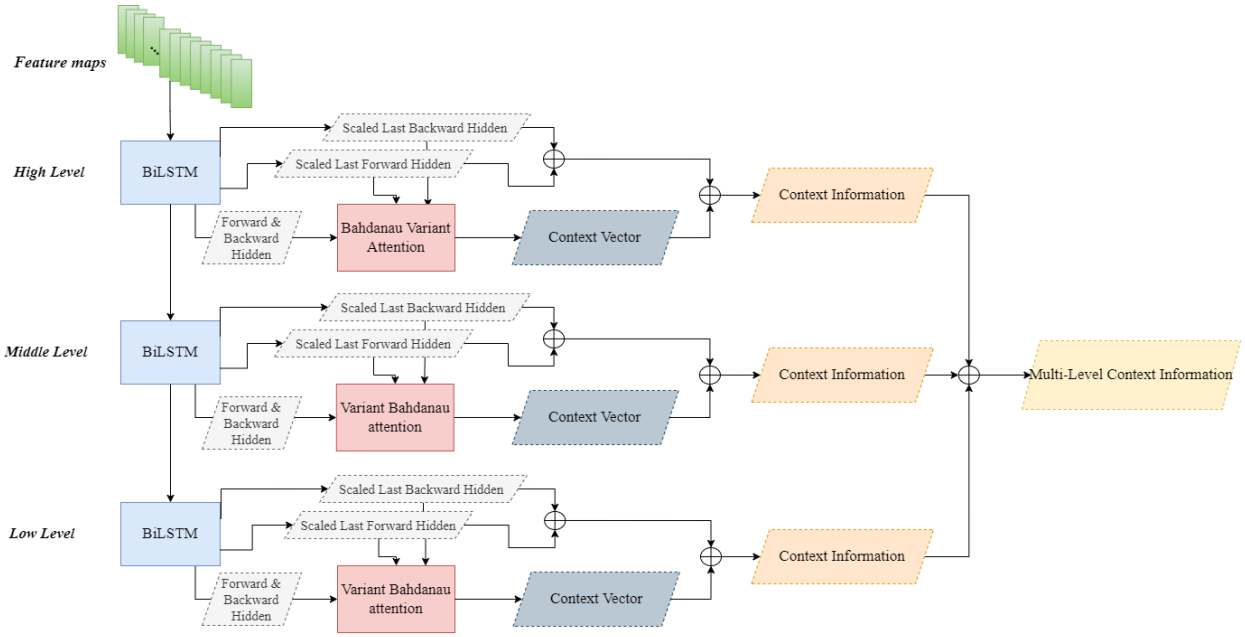


FIGURE 6. The architecture of multi-level context information.

TABLE 1. Hyperparameter for the classification tasks based on Part A of the BioVid heat pain database.

Layer	Units	Filter	Pool Size	Stride
Convolution 1D	32	5	-	1
Instance Normalization	-	-	-	-
Average Pooling	-	-	5	-
Convolution 1D	64	5	-	1
Instance Normalization	-	-	-	-
Average Pooling	-	-	5	-
Convolution 1D	128	5	-	1
Instance Normalization	-	-	-	-
Average Pooling	-	-	5	-
BiLSTMs	32	-	-	-
Scale	64	-	-	-
BiLSTMs	64	-	-	-
Scale	32	-	-	-
BiLSTMs	128	-	-	-
Scale	16	-	-	-
Dropout	-	-	-	-
Fully Connected	2	-	-	-

Notes: The ELU activation function is used after the convolutional and fully connected layers, except for the last fully connected layer where the softmax activation function is used. We remove 50% of information by dropout.

TABLE 2. Hyperparameter for the classification tasks based on the Emopain 2021 dataset.

Layer	Units	Filter	Pool Size	Stride
Convolution 1D	8	5	-	1
Instance Normalization	-	-	-	-
Average Pooling	-	-	5	-
Convolution 1D	16	5	-	1
Instance Normalization	-	-	-	-
Average Pooling	-	-	5	-
Convolution 1D	32	5	-	1
Instance Normalization	-	-	-	-
Average Pooling	-	-	5	-
BiLSTMs	8	-	-	-
Scale	48	-	-	-
BiLSTMs	16	-	-	-
Scale	24	-	-	-
BiLSTMs	32	-	-	-
Scale	6	-	-	-
Dropout	-	-	-	-
Fully Connected	2	-	-	-

Notes: The ELU activation function is used after the convolutional and fully connected layers, except for the last fully connected layer where the softmax activation function is used. We remove 50% of information by dropout.

others represent four pain classes. The temperature starts at 32°C as the initial temperature, then increases gradually but does not exceed 50.5°C. At that time, the participants feel the heat of pain until the pain was unacceptable. In addition, two intermediate levels are added. The experiment runs for 25 minutes with random pain levels. Each pain level is stimulated 20 pain times in 4 seconds. Following each pain level is a random rest duration of 8-12 seconds.

Data is recorded as frontal videos and different signal modalities. The signals include EDA, ECG, and EMG signals. EDA shows the skin conductance level index measured on the index finger and ring finger. In [2], this sensor is considered an excellent indicator of internal tension because the sweat glands are activated exclusively sympathetically. The ECG represents the action potential of heart rate measured from two electrodes, one on the upper right side and one on the lower left side of the body. The heart rate, the interbeat interval, and the heart rate variability features of the ECG represent a person's mental indication and emotional activity [2]. The EMG signal measures muscle activity and represents general psychophysiological arousal. The current dataset includes EMG at the trapezius muscle, located

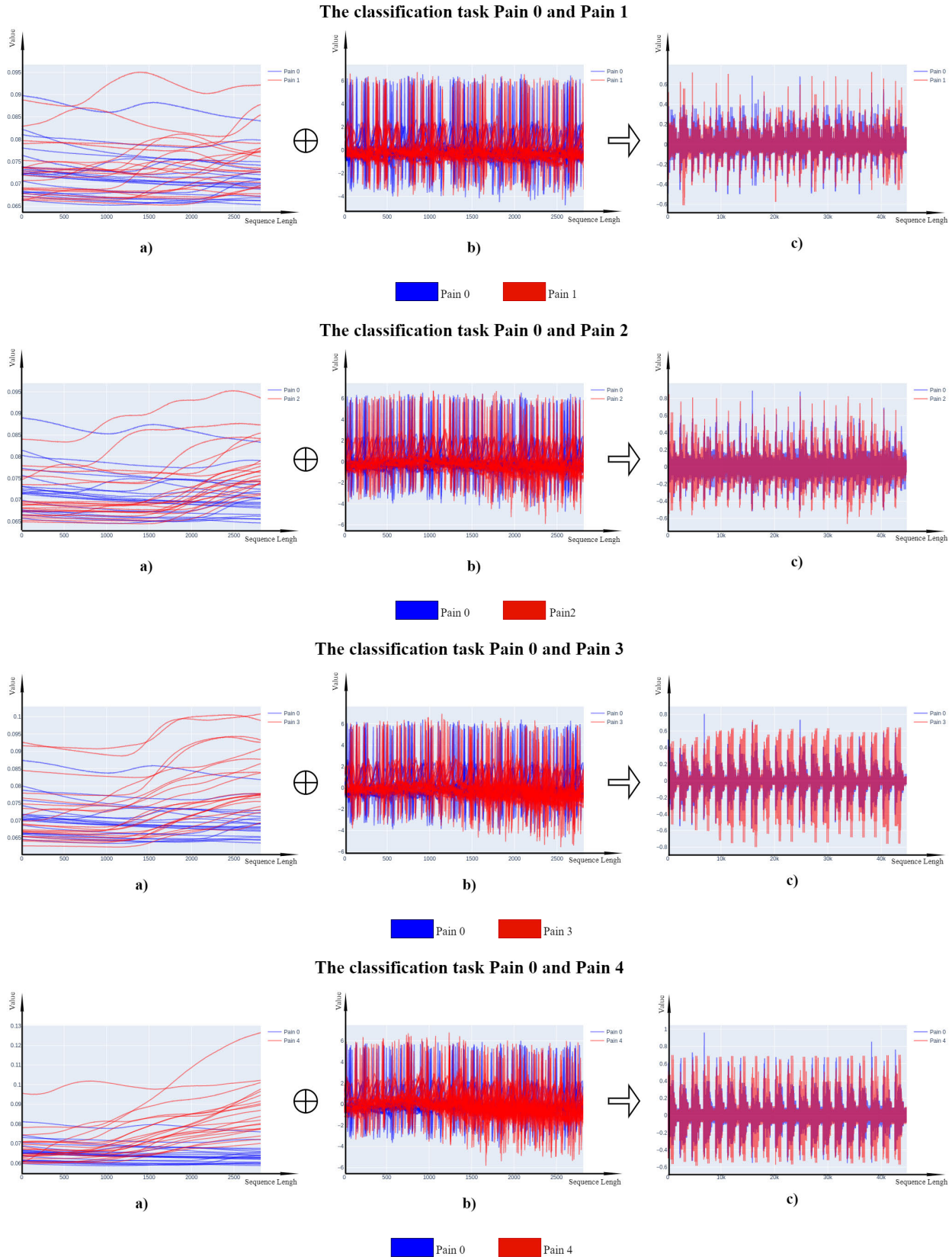


FIGURE 7. The first column a) is EDA signal input, the second column b) is ECG signal input, and the last column c) is multi-level context information in 67 subjects of LOSO cross-validation evaluation. Both EDA and ECG signals are 1-dimensional with a sequence length of 2816. The x-axis represents the sequence length and the y-axis represents the sequence value.

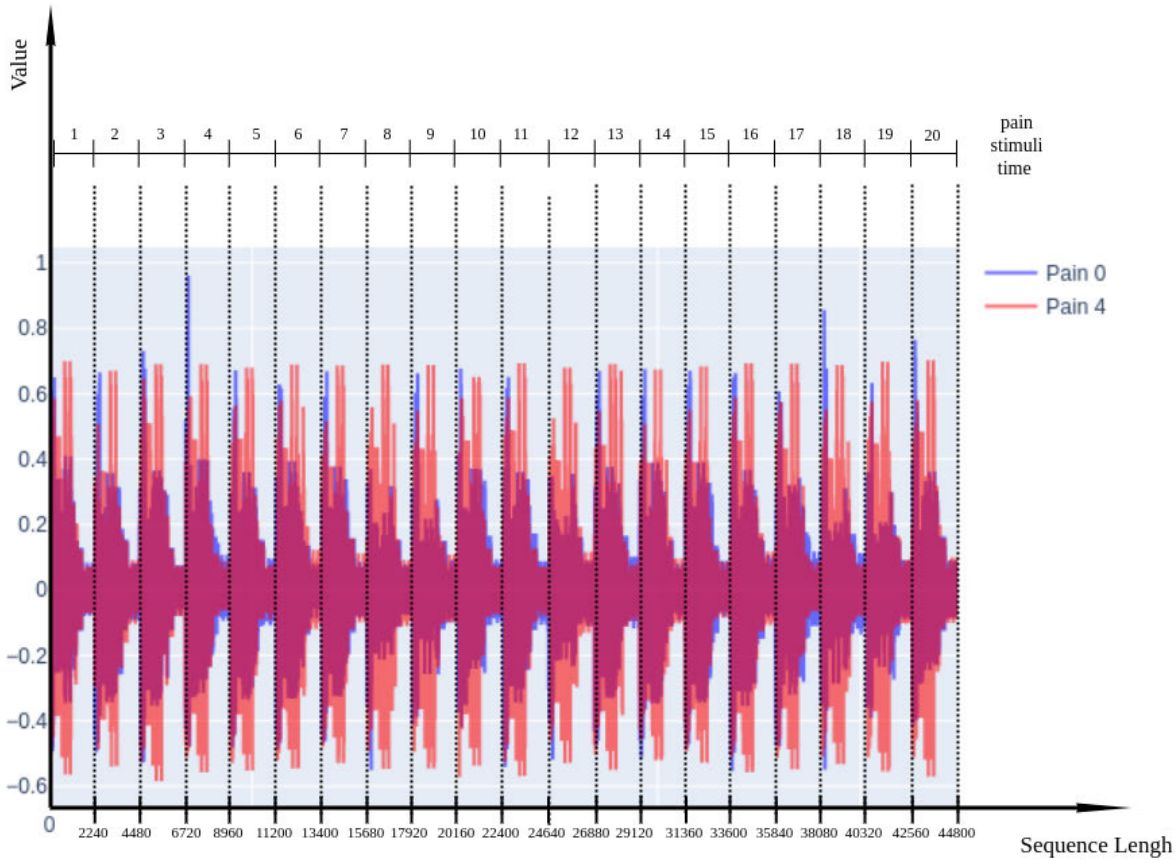


FIGURE 8. Detail illustration in the last column c) for the classification pain 0 and pain 4 of subject 071614-m-20.

posteriorly in the shoulder region. The activity of the trapezius is a sign of a high-stress level.

The database includes 90 participants equally divided into 3 age groups such as 18–35, 36–50, and 51–65 years. Each group is divided equally with 15 male and 15 female subjects. The database consisted of multiple parts with slightly different sizes and characteristics from 90 participants, the reports of previous studies are primarily based on Part A. To facilitate a comparison of the approaches, we evaluate them based on Part A of the BioVid Heat Pain Database in this study. Several subjects are missing due to technical problems during recording [6]. Therefore, only 87 subjects were available [6]. We describe the data structure of Part A in Table 3. It is balanced for classification tasks.

The signals are provided as both raw and preprocessed [24], [25]. For the preprocessed signals, a Butterworth filter with 20–250 Hz and 0.1–250 Hz is applied to the EMG and ECG signals. The EMG signal is additionally filtered by the Empirical Mode Decomposition technique [26] and its bursts are detected by the Hilbert Spectrum [27]. Each video has a sequence length of 5.5 seconds. Each signal has a sequence length of 2816, a time window of 5.5 seconds, and an epoch length of 512 Hz. For each subject, there are 20 random pain stimuli times for each level. The dataset consists of 87 subjects*20 times*5 levels = 8700 samples for the pain intensity recognition task.

2) EMOPAIN 2021 DATASET

The AffectMove 2021 Challenge [4] is divided into three tasks. Task 1 of the competition promotes protective behavior detection based on subjects with chronic musculoskeletal pain from the Emopain dataset [28]. This dataset is built on the deep knowledge of the automatic detection of affective/cognitive experiences without subjective evaluation factors. The Emopain 2021 dataset is a subset of the EmoPain dataset [28] suitable for building protection behavior detection technology [4]. It is used for Task 1 of The AffectMove 2021 challenge [4].

The dataset contains anonymized 3D full-body joint positions from videos and electromechanical signals from the back muscles of 19 subjects with chronic low back pain. The data has two classes Pain or No Pain. It consists of 5.827, 1.844, and 2.744 samples with training, validation, and testing sets, respectively. It also includes 51 features corresponding to 51 joint positions extracted from videos and four features corresponding to four muscle groups of electromechanical signals. We also describe the data structure in Table 4 and its distribution in Figure 9.

TABLE 3. Data structure of Part A of the BioVid heat pain database.

Object	Number
Subject	87
Age group	3 (18–35, 36–50, and 51–65 years)
Class	5 (Pain 0/ Pain 1/Pain 2/Pain 3/Pain 4)
Stimuli Time (per class and subject)	20
Sample	87*5*20 =8700
Time window	5.5s
Epoch length	512

TABLE 4. Data structure of the EmoPain 2021 dataset.

Object	Number
Training Set	5.827
Validation Set	1.844
Testing Set	2.744
Feature	51 (3-D joint from video) 4 (muscle group from EMG signal)
Class	2 (Pain/No Pain)

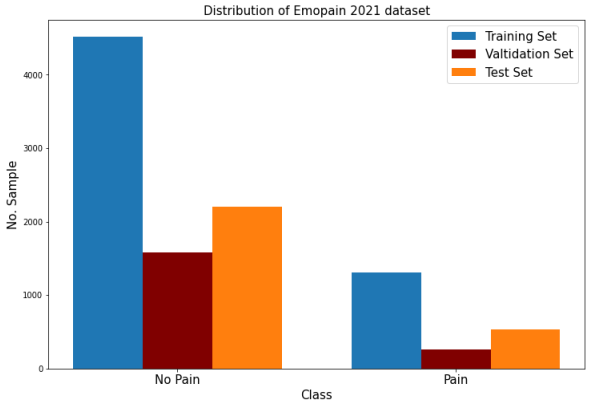


FIGURE 9. Distribution of the Emopain 2021 dataset.

B. PERFORMANCE ANALYSIS

1) BioVid HEAT PAIN DATABASE

We evaluate the proposed model based on Part A of the BioVid Heat Pain Database. We use the LOSO cross-validation method, which assigns a subject as a test, and the remaining subjects are used for training. The training process includes 67 times for 67 subjects and 87 times for 87 subjects. The average accuracy (in %) of the training process over the LOSO cross-validation evaluation is used for comparison with previous studies and the standard deviation is also provided. For pain recognition, we perform four binary classification tasks.

Experiments on other modalities are also performed. Table 5 presents the performance of the classification tasks for 67 and 87 subjects in the LOSO cross-validation. We conclude that EDA is of great significance in the proposed approach to pain recognition. The combination of EDA and ECG mostly has the best performance for classification tasks.

We experiment with architectures using only one level of context information including Low Level, Middle Level, and High Level. Table 6 compares the performance of levels for classification tasks on 67 subjects and 87 subjects in a LOSO cross-validation evaluation. The results show that multi-level context information performs more significantly than uni-level context information based on physiological signals.

The evaluation of the proposed model based on the highest pain classification compared with previous studies is presented in Table 7. In Table 5, we experiment on EDA signal and achieve an accuracy of 84.8B113.3% for 87 subjects and 87.6B117.4% for 67 subjects. Our results for the classification of Pain 0 and Pain 4 are also the best for EDA signals. The approach in [6] using 5-fold cross-validation evaluation with all modalities has a 4.2% lower average accuracy than our approach using LOSO cross-validation evaluation with EDA and ECG signals. Even though the approach in [16] employs EDA and ECG modalities with 10-fold cross-validation, our method still has a 2.15% better average accuracy. In addition, our method which only performs the combination of EDA and ECG achieves better results than the methods that combine the entire modality. In addition, the authors in [5] eliminate noise subjects who did not respond visibly to pain stimuli during training. There are few performance reports on this subset. However, we also report the performance of 67 subjects. Our approach has the highest performance on this topic for the classification of Pain 0 and Pain 4.

Table 8 presents the performance of the proposed approach compared to several previous approaches for classification tasks. The proposed approach mostly outperforms other methods for other classification tasks. However, the performance of the proposed method is slightly inferior to that of the method in [20]. The authors of [20] perform complex data preprocessing for physiological signals and data augmentation to increase the amount of data. By contrast, our method uses the available signals in the dataset and achieves competitive results for pain recognition.

In addition, we reveal Receiver Operating Characteristic (ROC) Curves for classification tasks with 67 subjects and 87 subjects in Figure 10 and Figure 11.

2) EMOPAIN 2021 DATASET

We also apply the proposed method using physiological signals of the Emopain 2021 dataset for binary classification. The training process is conducted with 3-fold cross-validation on the training set to evaluate the validation and the test sets. Let each fold k, we set up the weight $W_i^{(k)}$ for each class i in the training process to solve unbalanced data:

$$W_i^{(k)} = \frac{N^{(k)}}{2N_i^{(k)}}, \quad i = \{0, 1\} \tag{9}$$

where N is the specific number of samples.

Table 9 shows the effect of combining levels in our approach. The results prove that using multi-level gives better

TABLE 5. Performance based on Part A for the classification tasks in a LOSO cross-validation evaluation.

No. LOSO	Modality	0-1	0-2	0-3	0-4
67 subjects	EDA	**60.8±13.8**	**68.2±14.5**	77.1±14.9	87.6±17.4
	ECG	50.8±8.4	51.4±8.5	57.8±10.6	64.2±14.3
	EDA, ECG	60.5±12.8	67.4±15.0	**77.4±14.6**	**87.8±11.4**
87 subject	EDA	59.3±13.2	65.0±15.1	74.6±14.6	**84.8±13.3**
	ECG	50.1±6.6	50.6±7.2	54.8±9.3	61.2±13.0
	EDA, ECG	**59.5±12.4**	**65.7±14.7**	**75.2±14.6**	**84.8±13.3**

TABLE 6. Level performance comparison based on Part A of the BioVid heat pain database for the classification tasks in a LOSO cross-validation evaluation.

No. LOSO	Level	0-1	0-2	0-3	0-4
67 subjects	Low Level	60.6±12.7	67.4±14.4	77.1±14.1	87.2±12.1
	Middel Level	**60.6±13.6**	67.1±14.9	77.3±14.6	87.3±11.5
	High Level	58.5±13.1	66.8±15.1	76.2±15.4	86.9±21.1
	All Levels	60.5±12.8	**67.4±15.0**	**77.4±14.6**	**87.8±11.4**
87 subjects	Low Level	59.0±11.6	64.9±14.4	74.1±14.8	83.9±13.9
	Middel Level	59.2±12.5	65.3±14.9	74.5±14.6	84.3±14.0
	High Level	58.6±12.9	65.5±14.4	74.6±14.7	84.0±13.9
	All Levels	**59.5±12.4**	**65.7±14.7**	**75.2±14.6**	**84.8±13.3**

TABLE 7. Performance comparison based on Part A of the BioVid heat pain for classification pain 0 vs. pain 4.

Approach	Modality	CV Scheme	67 subjects	87 subjects
Werner et al. [6]	EDA, ECG, EMG +Video	5-FOLD CV	-	80.6
Werner et al. [29]	Video	LOSO	-	72.4
Kachele et al. [8]	EDA, ECG, EMG	LOSO	-	82.73
Werner et al. [5]	Video	LOSO	78.5	-
Lopez et al. [16]	EDA, ECG	10-FOLD CV	-	82.75±1.86
Lopez et al. [17]	EDA	LOSO	-	74.21 ± 17.54
Thiam et al. [20]	EDA	LOSO	-	84.57 ± 14.13
Wang et al. [18]	EDA, ECG, EMG	LOSO	-	83.3
Pouromran et al. [12]	EDA	LOSO	-	83.3
Thiam et al. [21]	EDA, ECG, EMG	LOSO	-	84.25±13.82
Our Approach	EDA, ECG	LOSO	**87.8±11.4**	**84.8±13.3**

TABLE 8. Performance comparison based on Part A of the BioVid heat pain for the classification tasks in a LOSO cross-validation evaluation.

Approach	Modality	CV Scheme	0-1	0-2	0-3	0-4
Werner et al. [6]	EDA, ECG, EMG +Video	5-FOLD CV	49.6	60.5	72.0	80.6
Werner et al. [29]	Video	LOSO	53.3	56.0	64.0	72.4
Lopez et al. [16]	EDA, ECG	10-FOLD CV	54.22±2.8	59.71±1.5	70.04±1.7	82.75±1.9
Lopez et al. [17]	EDA	LOSO	56.44±09.35	59.40±12.61	66.00±14.83	74.21 ± 17.54
Thiam et al. [20]	EDA	LOSO	**61.67 ± 12.54**	**66.93 ± 16.19**	**76.38 ± 14.70**	84.57 ± 14.13
Wang et al. [18]	EDA, ECG, EMG	LOSO	58.5	64.2	75.1	83.3
Our Approach	EDA, ECG	LOSO	59.5±12.4	65.7±14.7	75.2±14.6	**84.8±13.3**

outcomes than using uni-level in the context information based on physiological signals. Table 10 compare performance based on the Emopain 2021 Dataset. The previous methods are proposed for 3-D joint of video, and then four features of signals are used together. In [30], the authors propose 19 angle features and a statistic feature from the 3-D joints to enhance the performance on the validation set. They use the late fusion for 1-DCNN architecture with shortcut connections. In [31], the authors calculate the distance vectors between joints and the hips center, normalize by the distance between the shoulders center and the hips center. Random Forest is used for classification. In [32], the authors use statistical features for Random Forest and XGBoost models. In [33], they perform late fusion between PA-ResGCN for

TABLE 9. Level performance using physiological signals based on the Emopain 2021 dataset.

Set	Level	F1-P0	F1-P1	MCC	Acc
Validation	High Level	84.98	34.16	20.92	75.54
	Middle Level	87.49	33.79	21.56	78.96
	Low Level	86.84	33.72	21.12	78.04
	All Levels	**88.98**	**35.62**	**24.61**	**81.18**
Test	High Level	81.86	**24.77**	6.63	70.77
	Middle Level	84.65	23.36	8.74	74.42
	Low Level	84.50	22.51	7.73	74.16
	All Levels	**85.34**	23.01	**9.54**	**75.36**

Notes: F1-P0 and F1-P1 present F1 scores of No Pain and Pain, respectively.

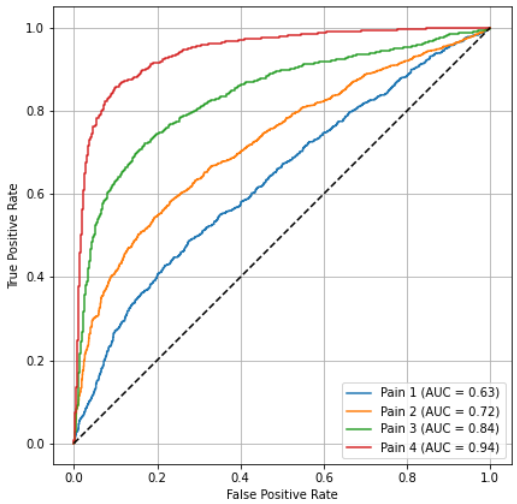


FIGURE 10. Receiver operating characteristic curves based on Part A of the BioVid heat pain for the classification tasks with 67 subjects.

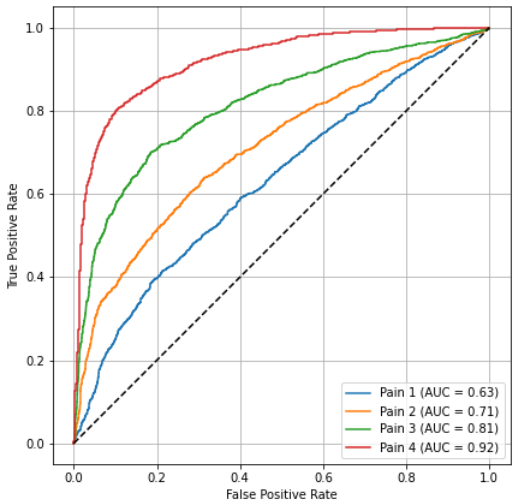


FIGURE 11. Receiver operating characteristic curves based on Part A of the BioVid heat pain for the classification tasks with 87 subjects.

3-D joints and CNN for signals. They also conclude that EMGs do not improve their performance.

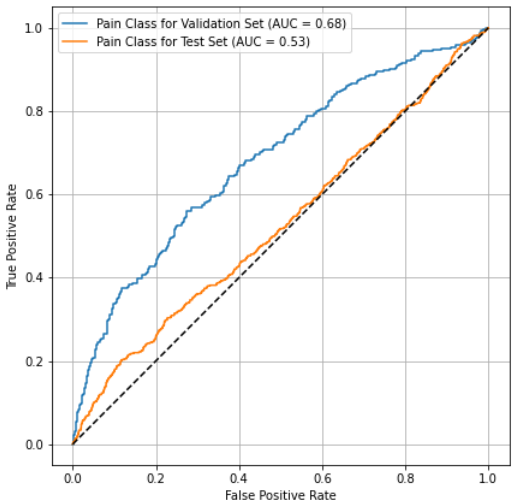


FIGURE 12. Receiver operating characteristic curves based on the Emopain 2021 Dataset.

However, the results of the proposed method are feasible. We also illustrate ROC on validation set and test set in Figure 12.

C. DISCUSSION

The method mainly applies basic architectures, including spatial, temporal architecture, and attention modules. With a simple architecture based on physiological signals available in datasets, our method offers competitive performance with previous methods. The proposed method is based on hidden sequence information to generate context information. Our experimental results demonstrate that using multi-level is more effective than using uni-level in the context information based on Part A of the BioVid Heat Pain database and the Emopain 2021 dataset. For Part A of the BioVid Heat Pain Database, our method using EDA achieves an accuracy of 87.6B117.4% 84.8B113.3% for the classification Pain 0 and Pain 4 in the LOSO cross-validation evaluation with 67 and 87 subjects, respectively. In addition, the combination of EDA and ECG achieves an accuracy of 87.8B111.4% and 84.8B113.3% for the classification Pain 0 and Pain 4 in the LOSO cross-validation evaluation with 67 and 87 subjects,

TABLE 10. Performance based on the Emopain 2021 dataset.

Methodolory	Features	F1-P0	F1-P1	MCC	Acc
Phan et al. [30]	Video, Signal	82.94	35.28	18.36	72.99
Dray et al. [31]	Video, Signal	89.	30.	23.	81.
D'Amato et al. [32]	Video, Signal	90.	48.	41.	84.
Radouane et al. [33]	Video, Signal	89.07	53.36	0.42	82.28
Our Approach	Signal	85.34	23.01	9.54	75.36

Notes: F1-P0 and F1-P1 present F1 scores of No Pain and Pain, respectively.

respectively. The proposed model achieves competitive performance with previous methods for other classification tasks.

The novelty of our method is the proposal of multi-level context information from physiological signals for pain recognition tasks. Latent information on sequences of physiological signals has the potential to be explored in classification tasks. Specifically, we explore hidden information for pain recognition in this study. Our approach replaces manual extraction methods that require highly specialized knowledge in medicine.

However, our method has not been optimally effective on the Emopain 2021 dataset and several classification tasks of Part A of the BioVid Heat Pain database. We experiment with common parameters for physiological signals and have not yet explored the optimal parameters for each physiological signal. The competitive results show that the parameters do not primarily affect performance.

The latent sequence information can be further explored and improved in the future to produce capable context information on physiological signals. The combination of significant context information creates superior multi-level context information.

V. 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.

REFERENCES

[1] P. Werner, D. Lopez-Martinez, S. Walter, A. Al-Hamadi, S. Gruss, and R. W. Picard, "Automatic recognition methods supporting pain assessment: A survey," *IEEE Trans. Affect. Comput.*, vol. 13, no. 1, pp. 530–552, Jan. 2022.

[2] S. Walter, S. Gruss, H. Ehleiter, J. Tan, H. C. Traue, S. Crawcour, P. Werner, A. Al-Hamadi, and A. O. Andrade, "The biovid heat pain database data for the advancement and systematic validation of an automated pain recognition system," in *Proc. IEEE Int. Conf. Cybern. (CYBCO)*, Jun. 2013, pp. 128–131.

[3] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, Sep. 2015.

[4] T. Olugbade, R. Sagoleo, S. Ghisio, N. Gold, C. D. C. Amanda, B. D. Gelder, A. Camurri, G. Volpe, and N. Bianchi-Berthouze, "The affectmove 2021 challenge—Affect recognition from naturalistic movement data," in *Proc. 9th Int. Conf. Affect. Comput. Intell. Interact. Workshops Demos (ACIIW)*, Sep./Oct. 2021, pp. 1–5.

[5] P. Werner, A. Al-Hamadi, and S. Walter, "Analysis of facial expressiveness during experimentally induced heat pain," in *Proc. 7th Int. Conf. Affect. Comput. Intell. Interact. Workshops Demos (ACIIW)*, Oct. 2017, pp. 176–180.

[6] P. Werner, A. Al-Hamadi, R. Niese, S. Walter, S. Gruss, and H. C. Traue, "Automatic pain recognition from video and biomedical signals," in *Proc. 22nd Int. Conf. Pattern Recognit.*, Aug. 2014, pp. 4582–4587.

[7] L. Breiman, "Random forests," *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, 2001.

[8] M. Kachele, P. Thiam, M. Amirian, F. Schwenker, and G. Palm, "Methods for person-centered continuous pain intensity assessment from bio-physiological channels," *IEEE J. Sel. Topics Signal Process.*, vol. 10, no. 5, pp. 854–864, Aug. 2016.

[9] Y. Chu, X. Zhao, J. Han, and Y. Su, "Physiological signal-based method for measurement of pain intensity," *Front. Neurosci.*, vol. 11, p. 279, May 2017.

[10] R. A. Fisher, "The use of multiple measurements in taxonomic problems," *Ann. Eugenics*, vol. 7, no. 2, pp. 179–188, 1936.

[11] S. Abe, *Support Vector Machines for Pattern Classification*, vol. 2. London, U.K.: Springer, 2005.

[12] F. Pouromran, S. Radhakrishnan, and S. Kamarthi, "Exploration of physiological sensors, features, and machine learning models for pain intensity estimation," *PLoS ONE*, vol. 16, no. 7, Jul. 2021, Art. no. e0254108.

[13] A. Smola and B. Schölkopf, "A tutorial on support vector regression," *Statist. Comput.*, vol. 14, no. 3, pp. 199–222, 2014.

[14] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, 2016, pp. 785–794.

[15] F. Pouromran, Y. Lin, and S. Kamarthi, "Personalized deep bi-LSTM RNN based model for pain intensity classification using EDA signal," *Sensors*, vol. 22, no. 21, p. 8087, Oct. 2022.

[16] D. Lopez-Martinez and R. Picard, "Multi-task neural networks for personalized pain recognition from physiological signals," in *Proc. 7th Int. Conf. Affect. Comput. Intell. Interact. Workshops Demos (ACIIW)*, Oct. 2017, pp. 181–184.
[17] D. Lopez-Martinez and R. Picard, "Continuous pain intensity estimation from autonomic signals with recurrent neural networks," in *Proc. 40th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2018, pp. 5624–5627.
[18] R. Wang, K. Xu, H. Feng, and W. Chen, "Hybrid RNN-ANN based deep physiological network for pain recognition," in *Proc. 42nd Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2020, pp. 5584–5587.
[19] S. D. Subramaniam and B. Dass, "Automated nociceptive pain assessment using physiological signals and a hybrid deep learning network," *IEEE Sensors J.*, vol. 21, no. 3, pp. 3335–3343, Feb. 2021.
[20] P. Thiam, P. Bellmann, H. A. Kestler, and F. Schwenker, "Exploring deep physiological models for nociceptive pain recognition," *Sensors*, vol. 19, no. 20, p. 4503, Oct. 2019.
[21] P. Thiam, H. Hihn, D. A. Braun, H. A. Kestler, and F. Schwenker, "Multi-modal pain intensity assessment based on physiological signals: A deep learning perspective," *Frontiers Physiol.*, vol. 12, Sep. 2021, Art. no. 720464.
[22] D. Bahdanau, K. Cho, and Y. Bengio, "Neural machine translation by jointly learning to align and translate," 2014, *arXiv:1409.0473*.
[23] I. K. M. Jais, A. R. Ismail, and S. Q. Nisa, "Adam optimization algorithm for wide and deep neural network," *Knowl. Eng. Data Sci.*, vol. 2, no. 1, pp. 41–46, 2019.
[24] S. Gruss, R. Treister, P. Werner, H. C. Traue, S. Crawcour, A. Andrade, and S. Walter, "Pain intensity recognition rates via biopotential feature patterns with support vector machines," *PLoS ONE*, vol. 10, no. 10, Oct. 2015, Art. no. e0140330.
[25] S. Walter, S. Gruss, K. Limbrecht-Ecklundt, H. C. Traue, P. Werner, A. Al-Hamadi, N. Diniz, G. M. D. Silva, and A. O. Andrade, "Automatic pain quantification using autonomic parameters," *Psychol. Neurosci.*, vol 7, pp. 363–380, Jan. 2014.
[26] A. Andrade, P. Kyberd, and S. Nasuto, "The application of the Hilbert spectrum to the analysis of electromyographic signals," *Inf. Sci.*, vol. 178, no. 9, pp. 2176–2193, May 2008.
[27] A. O. Andrade, S. J. Nasuto, and P. Kyberd, "Extraction of motor unit action potentials from electromyographic signals through generative topographic mapping," *J. Franklin Inst.*, vol. 344, nos. 3–4, pp. 154–179, May 2007.
[28] M. S. Aung, S. Kaltwang, B. Romera-Paredes, B. Martinez, and A. Singh, "The automatic detection of chronic pain-related expression: Requirements, challenges and the multimodal EmoPain dataset," *IEEE Trans. Affect. Comput.*, vol. 7, no. 4, pp. 435–451, Oct. /Dec. 2016.
[29] P. Werner, A. Al-Hamadi, K. Limbrecht-Ecklundt, S. Walter, S. Gruss, and H. C. Traue, "Automatic pain assessment with facial activity descriptors," *IEEE Trans. Affect. Comput.*, vol. 8, no. 3, pp. 286–299, Jul./Sep. 2017.
[30] K. N. Phan, S.-H. Kim, H.-J. Yang, and G.-S. Lee, "Multimodal convolutional neural network model for protective behavior detection based on body movement data," in *Proc. 9th Int. Conf. Affect. Comput. Intell. Interact. Workshops Demos (ACIIW)*, Sep. 2021, pp. 01–06.
[31] G. Dray, P.-A. Jean, Y. Maheu, J. Montmain, and N. Sutton-Charani, "The AffectMove challenge: Some machine learning approaches," in *Proc. 9th Int. Conf. Affect. Comput. Intell. Interact. Workshops Demos (ACIIW)*, Sep. 2021, pp. 1–5.
[32] V. D'Amato, L. Oneto, A. Camurri, and D. Anguita, "Keep it simple: Handcrafting feature and tuning random forests and XGBoost to face the affective movement recognition challenge 2021," in *Proc. 9th Int. Conf. Affect. Comput. Intell. Interact. Workshops Demos (ACIIW)*, Sep. 2021, pp. 1–7.
[33] K. Radouane, A. Tchechmedjiev, B. Xu, and S. Harispe, "Comparison of deep learning approaches for protective behaviour detection under class imbalance from MoCap and EMG data," in *Proc. 9th Int. Conf. Affect. Comput. Intell. Interact. Workshops Demos (ACIIW)*, Sep. 2021, pp. 1–8.

KIM NGAN PHAN received the B.S. degree from the Department of Mathematics and Computer Science, Ho Chi Minh City University of Science (VNUHCM), Vietnam, in 2020. She is currently pursuing the M.S. degree with the Department of Artificial Intelligence Convergence, Chonnam National University, South Korea. She joined the PR Laboratory, in March 2021. Her research interests include emotion recognition, sentiment analysis, and pattern recognition.

NGUMIMI KAREN IYORTSUUN received the B.Sc. degree from the Department of Mathematics and Computer Science, University of Mkar, Nigeria, in 2019. She is currently pursuing the master's degree with the Department of Artificial Intelligence Convergence, Chonnam National University, South Korea. She joined the Pattern Recognition Laboratory, in March 2022. Her research interests include depression intensity and treatment outcome estimation, pattern recognition, and computer vision.

SUDARSHAN PANT received the B.S., M.S., and Ph.D. degrees from Mokpo National University, South Korea. He is currently a Postdoctoral Researcher with Chonnam National University. His research interests include machine learning, affective computing, and healthcare AI.

HYUNG-JEONG YANG (Member, IEEE) received the B.S., M.S., and Ph.D. degrees from Chonbuk National University, Gwangju, South Korea. She is currently a Professor with the Department of Artificial Intelligence Convergence, Chonnam National University. Her main research interests include multimedia data mining, medical data analysis, social network service data mining, and video data understanding.

SOO-HYUNG KIM (Member, IEEE) received the B.S. degree in computer engineering from Seoul National University, in 1986, and the M.S. and Ph.D. degrees in computer science from the Korea Advanced Institute of Science and Technology, in 1988 and 1993, respectively.

Since 1997, he has been a Professor with the School of Electronics and Computer Engineering, Chonnam National University, South Korea. His research interests include pattern recognition, document image processing, medical image processing, and deep learning.