생리적 신호를 이용한 통증 인식을 위한 딥 러닝 네트워크

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Deep Learning Network Approach for Pain Recognition Using Physiological Signals

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ABSTRACT

Pain is an unpleasant experience for the patient. The recognition and assessment of pain help tailor the treatment to the patient, and they are also challenging in the medical. In this paper, we propose an approach for pain recognition through a deep neural network applied to pre-processed physiological. The proposed approach applies the idea of shortcut connections to concatenate the spatial information of a convolutional neural network and the temporal information of a recurrent neural network. In addition, our proposed approach applies the attention mechanism and achieves competitive performance on the BioVid Heat Pain dataset.

1. INTRODUCTION

Pain is one of the most common reasons why patients need medical attention [1]. Pain management is a challenging task in the medical field. Currently, several treatments for the pain are available. In [2], the authors use Butterworth to remove unwanted noise from electrocardiography (ECG) signal and skin conductance (EDA) signal. They demonstrate the effectiveness of a combination of convolutional networks and LSTMs based on ECG and EDA signals for pain assessment based on processed signals. In [3], the authors use a Butterworth filter to remove noise and artifacts. They use bidirectional LSTM to extract dynamic characteristics and create handcrafted features based on pre-processed signals. To classify pain intensity, they select 50 features from a combination of handcrafted features and features created by RNN that are inputs for Artificial Neural Network (ANN). In [4], the authors suggest a set of features to extract from the biomedical signals. They also propose to use the random forest as pain intensity classifier. [5], they employ the extracted features from physiological signals and the neural networks for a multi-task learning approach to classify pain. In this paper, we propose combining convolutional neural network (CNN) and recurrent neural network (RNN). In addition, we employ the shortcut connection of ResNet [6] and apply the attention mechanisms through global attention mechanism ideas [7] to improve performance with the input as the filtered signals in the BioVid Heat Pain database [8]. The following section describes our approach for pain detection based on physiological signals. Results of the experiment are expressed at the end of the paper.

2. DATASET

The BioVid Heat Pain Database [8] is multimodal data containing skin conductance (EDA), electrocardiography (ECG), electromyography (EMG) at trapezius muscle signals and facial action videos. Data has 90 subjects with five level heat stimuli (Baseline, T1, T2, T3, T4) under controlled conditions without causing skin burns. During the experiment, the temperature starts at 32C and must not exceed 50.5C. Each stimulus for each subject is randomly repeated 20 times and lasts about 4 seconds, resting between them of 8-12 seconds. Our approach employs the filtered signals in Part A filtered of BioVid Heat Pain Database, which has 87 subjects. We perform the binary classification task containing baseline pain and pain tolerance (T0 or T4). The binary classification dataset consists of 87 subjects x 20 times x 2 stimulus = 3480 samples in which we randomly select 1044 samples as the test set. Each time series sample has 2816 points with time windows of 5.5 seconds and a sampling rate of 512 Hz.

3. PROPOSED APPROARCH

A. Implementation

We implement neural network training on TensorFlows 2.5.

The cross-entropy function is used to represent the loss function, and the Adam algorithm is used to update the optimal weights for the training of the network. In this work, we evaluate performance based on the mean accuracy of the 6-folds cross-validation for binary classification task.

B. *Architecture*

CNN and RNN are two famous networks with the task of classification. The CNN layer performs the task of extracting spatial features of physiological signals, and the RNN layer with the role of capturing the temporal information of the data. We combine these outputs of two networks through the shortcut connection idea of ResNet architecture. We use one dimensional as input to the convolutional network along with the pooling and Batch Normalization layers (BN). The output is fed into bidirectional LSTM followed by layer normalization and Fully Connected layer (FC). The global attention mechanism is proposed in [7], which is the highlight that has performed excellently in enhancing the performance of our model. We apply the attention mechanisms through global attention mechanism ideas [7]. In this work, we train each signal individually before concatenating together into two FC layers. The final FC layer gives the classification probability of each class through the SoftMax activation function. Figure 1 depicts our architecture. In addition, we suggest the ensemble model for all models to improve the accuracy of the classification task. Figure 2 depicts this idea. In this work, we use k models, with each model representing per fold cross-validation. Each model has a different weight and a different prediction probability on the classes. The outputs of models are concatenated to perform an ensemble. Ensemble output gives the final probability, which is the maximum of the averaging probabilities as the formula below:

$$\hat{y} = argmax_j \left(p_j\right) = \left\{j \middle| p(j) = max_j \left(\frac{1}{k}\Sigma_{i=1}^{k} p_{ij}\right)\right\}$$

Where $\hat{y}$ is final prediction of class, p_j is the predicted probability of class j^{th} and p_{ij} is the predicted probability of classifier in fold i^{th} of class j^{th}.

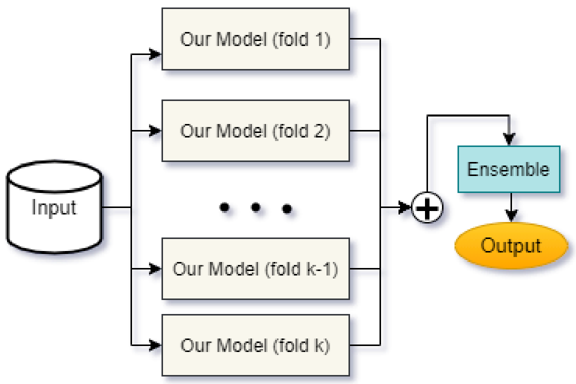

Fig 2. Ensemble procedure for our model.

C. *Results and Evaluation*

In this section, we employ mean and standard deviation accuracy for 6-fold cross-validation to evaluate performance. Moreover, results are improved through the ensemble model. The attention mechanisms were employed through global attention mechanism ideas [7]. We compare the performance of the proposed approach using the global attention mechanism [7] for the pain classification task. Table I shows the results using only EDA signal. The results show the outstanding effectiveness of the global attention mechanism [7] for our approach. Table I also shows this effect using all signals. The results show that the multimodal combination without using global attention [7] does not improve the performance of the proposed model. However, the results demonstrate excellent global attention [7] with the multimodal model. We also evaluate the performance based on the ensemble model for six-fold cross-validation. The results show 83.81% using the multimodal model and 82.18% using the unimodal from EDA signal.

TABLE I.
ACCURACY FOR BINARY CLASSIFICATION BETWEEN T0 AND T4 USING EDA SIGNAL AND ALL SIGNALS.

	k-fold	EDA signal	All signals
Non-Global Attention	1	74.33	58.72
	2	72.13	58.05
	3	74.04	58.52
	4	74.62	56.70
	5	76.15	59.67
	6	70.02	59.96
	Mean±STD	73.55±2.16	58.60±1.18
	Ensemble	76.05	61.21
Global Attention	1	81.80	82.18
	2	82.47	79.02
	3	79.02	81.90
	4	80.36	82.18
	5	81.99	82.85
	6	81.32	81.61
	Mean±STD	81.16±1.27	81.63±1.34
	Ensemble	82.18	**83.81**

The comparison of results between other methods and the proposed method using EDA signal is shown in Table II. The results show that the proposed method gives better performance than the previous research. In [4], the authors extract amplitude and variability features from EDA signal and employ random forest as pain intensity classifier. In [5], they employ the extracted features from EDA signal and the neural networks for a multi-task learning approach to classify pain. In [9], authors employ skin conductance deconvolution and explore through traditional models, and the results show accuracy based on logistic regression. Our model adopts popular deep learning approaches that give better performance using only EDA signal.

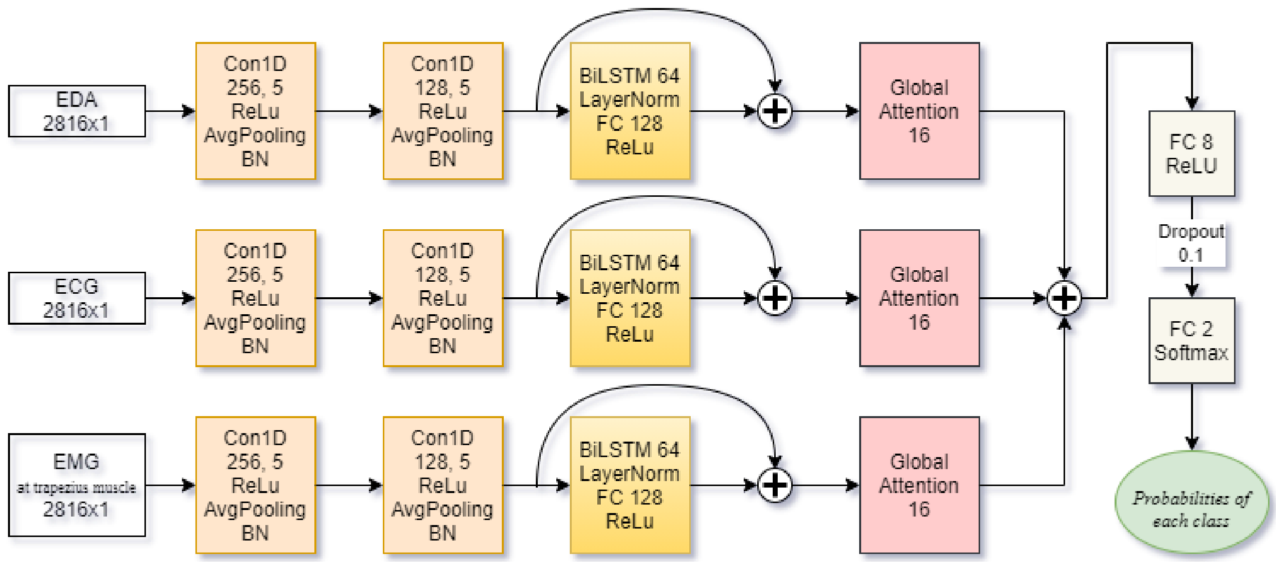

Fig 1. Our network overviews.

TABLE II
COMPARE ACCURACY FOR BINARY CLASSIFICATION BETWEEN T0 AND T4 USING EDA SIGNAL.

Method	Accuracy
Werner et al. [4]	73.8
Daniel et al. [5]	74.21±17.54
Daniel et al. [9]	79.98±0.92
Our Model	81.16±1.27
Our Ensemble Model	**82.18**

Table III also shows better performance when combining the unimodal model of each signal. In [3], the authors select 50 features from the fusion of dynamic characteristics of RNN and the handcrafted features for Artificial Neural Network (ANN). In [4], the authors use all physiological signals and videos as inputs of the random forest model to classify pain. In [10], the authors also use random forest methods. Our approach only uses filtered signals as inputs in BioVid data for the proposed model. We have three filtered signals containing EDA, ECG and EMG signals for the deep learning network application. The results have shown that deep learning is effective in classifying pain.

TABLE III
COMPARE ACCURACY FOR BINARY CLASSIFICATION BETWEEN T0 AND T4 USING ALL SIGNALS.

Method	Modality	Accuracy
Run et al. [3]	All physiological signals	83.3
Werner et al. [4]	All physiological signals	76.6
Werner et al. [4]	All physiological signals and videos	80.6
Kachele et al. [10]	All physiological signals and videos	83.1
Our Model	All physiological signals	81.62±1.34
Our Ensemble Model	All physiological signals	**83.81**

4. CONCLUSION

We propose the approach to classify between baseline pain and pain tolerance (T0 or T4) based on Part A of BioVid Heat Pain. The proposed method combines a convolutional neural network (CNN) and a recurrent neural network (RNN) as input for the attention mechanism. The attention mechanisms through global attention mechanism [7] and ensemble model with six models improve performance. The experimental results achieve 83.81% accuracy using all signals and 82.18% accuracy using EDA signal. In addition, we also get 81.62±1.34% using all signals and 81.16±1.26 % accuracy using EDA signal for 6-folds cross-validation evaluation. The proposed approach employs deep learning networks to improve performance using filter physiological in BioVid Heat Pain Database. In the future, we will implement more the extracted features from the preprocessed signals for the proposed model.

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