Stress Classification and Personalization: Getting the most out of the least

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Abstract—Stress detection and monitoring is an active area of research with important implications for the personal, professional, and social health of an individual. Current approaches for affective state classification use traditional machine learning algorithms with features computed from multiple sensor modalities. These methods are data-intensive and rely on handcrafted features which impede the practical applicability of these sensor systems in daily lives. To overcome these shortcomings, we propose a novel Convolutional Neural Network (CNN) based stress detection and classification framework without any feature computation using data from only one sensor modality. Our method is competitive and outperforms current state-of-the-art techniques and achieves a classification accuracy of 92.85% and an $f_1$ score of 0.89. Through our leave-one-subject-out analysis, we also show the importance of personalizing stress models.

Index Terms—effective states, stress detection, sensor system, wearables

I. INTRODUCTION

Stress describes bodily reactions to perceived physical or psychological threats [1] and is defined as the transition from a calm state to an excited state triggering a cascade of physiological response [2]. In the United States of America, around 77% people suffer from headaches and insomnia for reasons related to stress, and there has been a steady increase in the number of people suffering from stress-related issues each year [3]. Furthermore, stress plays a critical role in many health problems, such as depression, anxiety, high blood pressure, heart attacks, and stroke [4]. Stress also influences a person’s decision-making capability, attention span, learning, and problem-solving capacity [5]. Stress detection and monitoring can help prevent dangerous stress-related diseases. Towards this end, in this paper we propose, a novel Convolutional Neural Network (CNN) based framework for stress detection and classification, which uses raw Electrodermal Activity (EDA) sensor data without feature computation. Our approach is competitive with other state-of-the-art methods and does not suffer from many limitations inherent in earlier works. Figure 1 shows the general overview of a stress detection system used for real-time interventions to support the health of an individual. In this paper, we implement the stress classification pipeline, and in the future, we aim to use our classification model for strategic real-time interventions.

Usually, for stress detection and classification data from multiple sensor modalities such as heart rate variability (HRV), body acceleration (ACC), skin temperature, electrodermal activity (EDA), blood volume pulse (BVP), respiration rate, and electrocardiogram (ECG) are used to compute a large number of statistical and structural features to train machine learning algorithms. In [7], the authors computed 67 features from 7 sensor modalities to train a stress classification model with the best accuracy of 92.28%. Using the same dataset, the authors in [4] used Deep Neural Networks (DNN) and 40 statistical features to achieve an accuracy of 95.21%. In [5] the authors used statistical features and representation learned by a deep learning model as features to train the stress classification model with accuracy up to 92%. Feature selection was used to reduce the number of features to 9 for the best possible classification accuracy. Furthermore, some works have also explored ways not to use electrodermal activity for stress classification since most commercial smartwatches and smart health devices don’t have sensors to measure galvanic skin response. In [9], authors used data from the built-in smartphone accelerometer sensor to identify activity that corresponds with stress levels and achieved an accuracy of 71%. Also, in [10] data from a com-
mercial smartwatch was used for binary stress classification with accuracy up to 83%.

Using data from multiple sensors and computing a large number of features to train machine learning algorithms for stress classification has several disadvantages. Using numerous sensor modalities makes the system design complicated and expensive and hence unfit to be used in everyday lives. Also, sensors need power to operate, and more sensors draw more power, which is a big issue in battery-powered wearable systems. Computing features require domain knowledge, and extensive testing is needed to find the best set of features for optimal classification performance. Furthermore, computing a large number of complex features makes the classification algorithm less efficient in terms of run-time, energy, and memory. Besides, feature selection is needed to select the most meaningful features and adds an extra processing step to an already complex machine learning pipeline. Motivated by these drawbacks of multi-modal feature-based stress classification algorithms, in this paper, we propose a CNN-based stress detection and classification system which takes raw EDA sensor segments as inputs and learns and select the dominant features automatically during the training process. Our primary objective is to implement a stress detection and classification system using only the EDA data. The secondary goal was to explore the personalization of stress models. Perception and effects of stress are subjective in nature. The same external stimuli can have a varying degree of effect on different individuals in terms of stress and emotional arousal. Hence, we also investigate whether stress detection algorithms need personalization or not.

II. METHODOLOGY

A. Dataset

The Wearable Stress and Affect Detection (WESAD) dataset [7] is a publicly available dataset with ECG, EDA, BVP, respiration (RESP), skin temperature (TEMP), and motion (Acceleration) (ACC) sensor data obtained from the RespiBan (chest-worn) and Empatica E4 (wrist-worn) devices. The dataset was collected from 15 subjects (3 female) in a laboratory setting, and each subject experienced three main affect conditions: baseline or normal (neutral reading), stress (exposed to Tier Social Stress Test (TSST)), and amusement (watching funny videos). In our analysis, we only use the EDA data from the Empatica E4 sampled at 4Hz. Approximately the length of the stressed condition was 10 minutes, amusement 6.5 minutes, and baseline situation was 20 minutes.

B. Segmentation and Normalization

For each subject, we have approximately 37 minutes of EDA data. We segment the EDA data for the three affective states into 60 seconds overlapping segments with 50% overlap between consecutive segments. We settled on the window size of 60 seconds because of available literature that has also used 60 seconds window size for the WESAD dataset [4]–[7]. Before segmentation, we normalize the data for each subject using the min-max normalization to spread the data in the range of [0, 1]. After segmentation, we obtain 564 samples for the baseline class, 311 samples for the stressed class, and 165 samples for the amusement class. In our analysis, we have not used any method to deal with class imbalance and machine learning models are trained on the imbalance data for the worst case scenario.

C. Convolutional Neural Network

Data-driven learning algorithms learn associations between input and outputs directly from the sensor data without feature computation. These methods learn features and classifier simultaneously from the sensor data. A convolutional neural network (CNN) is a data-driven learning algorithm capable of learning local dependency and scale invariance in the input data without feature computation. In CNN, the convolution operation is used between the input and a weight matrix or filters to assemble complex features by successively learning smaller and simpler features. Consequently, CNN is suitable for our approach towards stress detection and classification, and hence we have used 1D CNN as the learning algorithm in our work. We have used a ConvNet architecture composed of two 1D convolutional layers with 100 filters each and kernel size of 5 and 10 respectively. This is followed by a global max-pooling layer and two fully connected layers with 128 and 64 neurons. We also have drop-out layers after each fully connected layer with drop-out values 0.3 and 0.2. The output layer has Softmax activation, and all other layers have ReLU [11] activation. Figure 2 shows the graphical representation of the proposed CNN used in this paper.
D. Hyperparameters and Training

The hyperparameters in our framework were selected after extensive trial and error. The CNN models were trained for 200 epochs with a batch size of 32 and a fixed learning rate of 0.001. Out of 876 samples in the dataset, 657 or 75% was included in the training set, and 219 or 25% belonged to the test set. For bi-affective state classification, data from the baseline (not-stress) and stressed classes were used to create the training and test sets. For tri-affective state classification data for all three classes: baseline, stressed, and amusement were used to create the training and test sets.

III. RESULTS AND OBSERVATIONS

Due to the lack of space, we have omitted training curves of the CNN models and we want to confirm we observed no overfitting during training.

A. Stress Classification

First, we present the results for the bi-affective state classification i.e., the binary case of stress Vs. not-stress classification. The trained CNN model achieved the best classification accuracy of 94.8% on the training set and 90.9% on the test set. Table I shows the value of other performance metrics.

| Dataset  | Accuracy | Precision | Recall | f1-Score |
|----------|----------|-----------|--------|---------|
| Training Set | 94.8% | 0.96 | 0.88 | 0.92 |
| Testing Set | 90.9% | 0.91 | 0.82 | 0.87 |

In the second case, we consider the tri-affective state classification, a multi-class classification problem with 3 classes: stress, not-stress, and amusement. Table II shows the values of performance metrics for this case. Note that the performance of the CNN model has decreased in the tri-affective case compared to the bi-affective case. We suspect this is because the model doesn’t have enough training samples to learn the distinction between the three classes.

| Dataset  | Accuracy | Precision | Recall | f1-Score |
|----------|----------|-----------|--------|---------|
| Training Set | 85.1% | 0.83 | 0.79 | 0.80 |
| Testing Set | 82% | 0.82 | 0.72 | 0.76 |

Furthermore, to account for the variance in performance, we conducted 10—fold cross-validation for both cases of affective state classification. Table III shows the average classification accuracy and f1-score for bi-affective and tri-affective cases.

| Dataset  | Accuracy | f1-Score |
|----------|----------|---------|
| Bi-affective Training Set | 93% | 0.9 |
| Bi-affective Testing Set | 90% | 0.86 |
| Tri-affective Training Set | 94% | 0.79 |
| Tri-affective Testing Set | 90% | 0.75 |

Finally, we present comparisons of our results with other state-of-the-art works on stress classification with the WE-SAD dataset in Table IV. WE-SAD dataset has the following modalities ACC, EDA, TEMP, ECG, BVP, and RESP, and is represented by All in the table. All other compared approaches, details in [1], computes statistical or representational features from sensor data to train stress classification models. Our method, does not involve computation intensive feature computation and selection stages and uses the raw sensor data for training. Also, our approach is based on CNNs whereas compared methods are based on neural networks as well as statistical learning algorithms. We found our proposed approach to be competitive with state-of-the-art methods with the added advantage of being data-driven without needing any specialized domain knowledge for feature computation and selection.

| Method | Model Type | Modalities | Accuracy (%) | f1-Score |
|--------|------------|------------|--------------|---------|
| [1]    | Feature    | All        | 93           | 0.9     |
| [2]    | Feature    | EDA        | 91.60        | -       |
| [3]    | Feature    | EDA        | —            | 0.92    |
| Our’s  | Data       | EDA        | 95.21        | 0.94    |

B. Personalization of Stress Models

To investigate the subjective nature of stress and determine whether we need personalized models for stress detection and classification, we present the results of leave-one-subject-out (LOSO) analysis on the binary WESAD dataset. In LOSO analysis, data from one subject is removed from the training set and kept as the test set to evaluate the trained machine learning model. The WESAD dataset was collected from 15 subjects and we present the results of LOSO analysis for each subject. Figure II shows the classification accuracy and figure III shows the f1-score of the trained models on the test and training sets. The x-axis represents the subject whose data was not included in the training set and was used as the test set. Based on our results, we can confirm that stress is subjective, and the same external stimuli can have varying effects on different individuals. On the test data for left out subjects S2, S3, S7, S11, S14, and S17 the trained models performed poorly, but for subjects S4, S5, S6, S8, S9, S13 and S15 the trained model performed better compared to the training set. Furthermore, the performance of the model on the test data for left out subjects S10 and S16 was similar to that on the training set. The discrepancies in the results of LOSO analysis can be attributed to many different reasons such as physical characteristics, emotional endurance, stress management skills, personality traits, and noise in the sensor data. For example, subject S3 was looking forward to stress conditions and was cheerful during data collection. Subject S5 might have fallen asleep during the first meditation phase and subject S6 had a stressful week, and the study was relaxing and not very stressful. Also, subject S8 already had a stressful day before
the study and felt cold in the study room. These observations suggest that to better account for the differences between individuals towards the perception of stressful events and to build a general model for stress classification personalization of stress models is needed.

The authors in [4] also used LOSO for cross-validation and were able to achieve a classification accuracy of 95.21% and f1-score of 0.94 with a neural network trained on features data computed from all sensor modalities. In [8] the authors, computed various features from EDA data, and were able to achieve an average f1-score of 0.89 with the XGBoost algorithm. Our LOSO analysis is based on just EDA data without any feature computing, and on average, across subjects, our method has the classification accuracy of 85.44% and f1-score of 0.75.

Fig. 3. Classification accuracy on the training and test sets for leave-one-subject-out analysis. The x-axis represents the subject whose data was not included in the training set and was used as the test set.

Fig. 4. f1-score on the training and test sets for the leave-one-subject-out analysis to investigate the subjective nature of stress. The x-axis represents the subject whose data was not included in the training set and was used as the test set.

To personalize the stress models for left-out subjects whose test set performance was lower than the training set, we retrained the machine learning models on the left-out subject data. Starting from 1 sample from the test set, we successively increased the number of samples used for re-training the model until the performance of the model on the test set was greater or equal to that on the original training set. Table V shows the number of samples needed for each left-out subject and the final test set accuracy after re-training. The performance of the model on the test set increased significantly after re-training, suggesting we need personalized stress models for maximum performance.

### Table V

| Subject | Original Test Set Accuracy | Total Samples | Re-training Sample Size | Final Test Set Accuracy |
|---------|---------------------------|---------------|-------------------------|------------------------|
| S2      | 76.8                      | 56            | 43                      | 96.4                   |
| S3      | 67.9                      | 56            | 40                      | 85.9                   |
| S7      | 84.5                      | 58            | 42                      | 98.3                   |
| S11     | 66.1                      | 57            | 52                      | 98.3                   |
| S14     | 55.9                      | 69            | 42                      | 94.9                   |
| S17     | 57.4                      | 61            | 43                      | 93.4                   |

**IV. Conclusion**

In this work, we proposed a novel CNN-based stress detection and classification framework that uses raw EDA sensor data without feature computation and selection for affective states (stressed vs. normal vs. amusement) classification. We used the EDA data because EDA is found to be the best indicator of stress. Our approach can be adapted to include other sensor modalities for possible performance improvement also extended to other datasets. We also showed the need for a personalized stress model with our leave one subject analysis. Our approach is competitive with other state-of-the-art methods and does not suffer from many disadvantages such as feature computation and selection, multi-modal input data, and complex system design.

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