Investigating Feasibility of Stress Detection from Social Media Content through Wearables

Kalliopi Tsiampa*, Lili Zhu§, Petros Spachos§*, and Vassilis P. Plagianakos *
*Department of Computer Science and Biomedical Informatics, University of Thessaly, Greece
§School of Engineering, University of Guelph, Guelph, ON, Canada

***Abstract*—The plethora of online applications and mobile communication systems helps in the increase of the everyday usage of social networks. More people tend to use social media and join social networks. At the same time, several people suffer from mental stress while they either receive or create social media content. In this work, we examine the feasibility of detecting stress related to social media content, with the use of wearable devices. We use Electrodermal Activity (EDA) signals collected from wrist-based devices and we examine any correlation between them and the social media content. We conducted experiments in different environments with self-reported data from the users. According to preliminary results, the relationship between EDA and stress levels related to social media content can be identified.**

***Index Terms*—Electrodermal activity, stress detection, wrist devices, social media interaction.**

I. Introduction

Over the years, the usage of social media has increased. People use them for a plethora of applications, from simple forms of communication and message exchanges to reading the news, advertising, and marketing. During the recent pandemic, people used social media to keep up to date with global news, to communicate, and to be entertained [1]. The use of social media nowadays continues to be high and growing. According to statistical studies 4.48 billion people currently use social media worldwide, up more than double from 2.07 billion in 2015, while the average social media user engages with an average of 6.6 various social media platforms [2]. It is clear that the popularity of social media has increased dramatically in recent years. More and more people are sharing their daily lives and communicating with friends on these platforms.

Meanwhile, according to studies, the anxiety and stress many social media users are experiencing are closely related to how people interact with them [3]. Social media users can either receive content and/or create content while using social media that reflects their mood, stress level, and physiological state. Early detection and prediction of high stress level states can help decrease wellness challenges, such as depression. However, detection accuracy is related to the accuracy of the data as well as the amount of data available for proper processing and prediction.

Wearable devices, such as smartwatches, can provide large amounts of continuous data related to the user. These devices are equipped with sensors that can collect different physiological signals related to stress levels [4], [5], such as Electrocardiogram (ECG) [6], [7], Photoplethysmogram (PPG) [8], [9], and more recently Electrodermal Activity (EDA) [10], [11], while they can also transmit the data to a powerful smartphone or even to the cloud for further processing and analysis. Wearable devices are mainly used to monitor heart rate, the amount and type of exercise a person does, but also the calories a person burns in a day.

In this work, we investigate the feasibility of stress detection related to social media content. We collect EDA signals from the wrist of the users while they use social media, and further investigate the correlation between peaks in EDA signals and anxiety levels. We clean and process the signals and we analyze the results. According to preliminary experimental data, stress related to social media content can be detected, while social media usage without high stress levels does not affect the analysis.

The rest of this paper is organized as follows: the related work is reviewed in Section II. The proposed system overview is discussed in Section III, while the methodology that we followed is presented in Section IV. The results and the discussion are available in Section V. We conclude this work in Section VI.

II. Related Work

In [12], data collected from smartphones and a wearable device, specifically an Oura Ring, are combined to identify whether people are suffering from or at risk of developing mental disorders. For this purpose, 60 adults with an iPhone device were invited to participate in the survey. They were given an Oura Ring, while a developed smartphone application was installed on their mobile phones for data acquisition. The application recorded the duration and frequency of smartphone usage, while also collecting data related to GPS and the users' location. Measures from the ring regarding steps, sleep patterns, and Heart Rate Variability (HRV) were taken. According to the results, there is a growing body of research demonstrating that digital phenotyping data may enable the identification of people suffering from or at risk of developing mental disorders, in some cases even before symptoms are detectable using traditional methods (surveys and questionnaires). In this study, they are using ACC, HRV sensors. Also, they take into consideration the sleep patterns of each person. Comparing all those signals with GPS data acquired from smartphones, their aim is the detection of mental health problems. The models in these studies showed significant negative correlations between the variability of locations visited by the subjects and the depression symptoms they displayed. Moreover, there were significant positive correlations between total sleep time and depressive symptoms, bedtime and depression, wakefulness after sleep onset and anxiety, and HRV and anxiety. A model consisting of a smartphone and a wearable device combined with self-reported mood assessments provided the strongest predictor of depression.

Additionally, EDA has been used in different scenarios with different target groups to identify their emotional state. In [13], they focused on EDA while aiming to discriminate stress from cognitive load in an office environment. In this study, a collective of 33 male subjects underwent a laboratory intervention that included mild cognitive load and two stress factors, which are relevant at the workplace: mental stress induced by solving arithmetic problems under time pressure and psychosocial stress induced by social-evaluative threat. The experiment aims to distinguish between a state of mental and psychosocial stress from a state of (mild) cognitive load and not between a state of rest (doing nothing) and a state of stress. The paper focuses on single-sensor data acquisition, even though multimodal signals are also acquired. The maximum accuracy they managed to get was 82.8%, with leave-one-person-out cross-validation, through the monitoring of the EDA signals. As it can be inferred, EDA measurements could prove to be an accurate prediction of stress in subjects. In [14], a healthy group of 30 subjects, consisting of 25 males and 5 females, had to solve tasks (logical puzzles, calculations, memory tasks) with a set time limit. The subjects wore headphones through which different sounds were used to distract them. The experiment took place in a quiet room with a computer, while the subjects were in a relaxed state, so experiments in real-world conditions would vary compared to this controlled environment. Three different types of sensors were used to measure heart rate, respiration, and skin conductance (SCL), so this experiment did not have a single-sensor approach. Also, social pressure was induced on the subjects during the memory task. The accuracy of the study was close to 80%.

In [1], they are aiming to describe the impact social media has on the mental health of the general population, focusing on the inaccurate and misleading information that was flooding the internet during those times. In [15], they showed that problematic use of social media worsened the fear of the pandemic as well as depressive symptoms. According to [16], frequently using social media leads to higher levels of anxiety, depression, and social isolation when compared to less exposure. Moreover, social media usage before bed could lead to sleep problems as well [17]. Sleep disturbances and low sleep quality could in turn lead to mental health problems such as anxiety, depression, and psychological distress. Social media apps are used by a large number of young adults, 60% of whom report using screens 1 hour before bedtime [18], while according to studies 81% of young people use social media [18].

In this work, we focus on EDA collected from wrist devices. In our previous work [19], we showed that EDA captured from the wrist has less noise and therefore we can better analyze the signals. According to the study, compared to PPG and ECG, EDA provides the highest accuracy in stress classification. Moreover, when gender information is available, the accuracy of EDA is even higher in women. Therefore, EDA is the primary candidate when performing stress screening.

In comparison with the related work, in this paper, we try to identify any emotional effect of social media content on individuals. We use the EDA signals collected from the wrist and we examine any potential correlation.

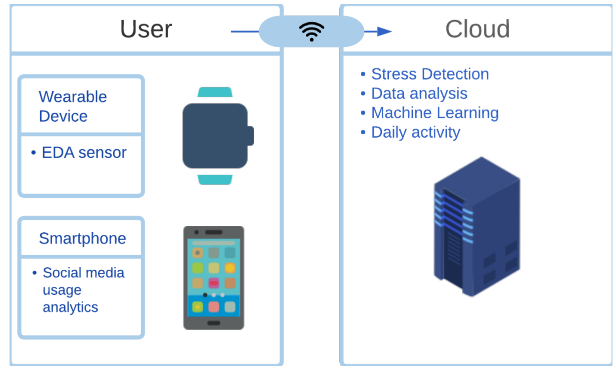


Fig. 1: Overview of the system architecture.

III. System Overview

The proposed system consists of a wearable device, a smartphone, and a cloud service. As shown in Fig. 1, the raw EDA signals are collected from the wearable device, whilst we use the smartphone to employ social media usage analytics so as to determine the exact hours the subject used each social media application. The EDA signals as well as the usage analytics are uploaded using WiFi to the cloud and will be ready to be analyzed and processed.

A. Electrodermal Activity (EDA)

EDA signals are used to perceive the emotional state of a person. Fluctuations in these signals can show whether a person is happy, angry, anxious, and so on. EDA has been used to assess people's emotions and reactions to stress in various scenarios. Moreover, EDA is a non-invasive method to monitor stress. It can be measured from different parts of the human body, such as the fingers or wrist. EDA represents the skin's capacity to conduct a flow of electrical current. Using EDA sensors we can measure the conductance of the skin (skin conductance response - SCR) and therefore analyze the emotional response of a person to a certain event. For example, if something causes pain to a person a sympathetic response will be elicited by the sweat glands and the secretion of sweat will be increased. Although this increase might be small, sweat contains electrolytes, which increase electrical conductivity, thus lowering the electrical resistance of the skin. These changes are perceived using the EDA sensors. The wrist does not represent the best place for an EDA sensor to be located, but it is the most convenient location as a wearable

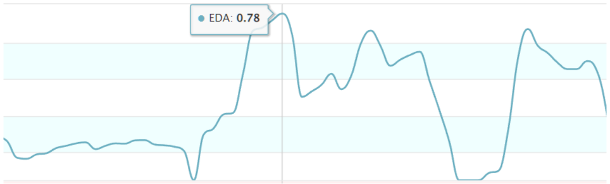


Fig. 2: Phasic component of an EDA signal.

on the wrist does not interfere with the daily activities of the person wearing it [20].

The EDA signal has two components, the phasic component, and the tonic component. The phasic component, shown in Fig. 2, includes the rapid and smooth transient events resulting either from a sympathetic reaction invoked by external stimuli (event-related SCR) or from spontaneous skin conductance responses (non-specific SRCs). The tonic component of the EDA signal is the skin conductance level (SCL) and it includes the slow spontaneous electrical fluctuations of the sweat glands [20]. It is the baseline of the EDA signal [19]. The changes of the SCR are more rapid and distinct than the SCL, therefore we can observe the peaks of the signals.

The tonic component of the EDA signal (SCL) does not exhibit any substantial phasic activity. It is a signal that rises gradually and it is not typically associated with external stimuli to the subject [21]. The non-specific conductance responses (NS-SCRs) usually occur one to five seconds after the user receives the stimulus [19]. The latency and amplitudes of SCR in response to stimuli are the main focus of researchers, particularly the ER-SCR, which is significantly related to a stimulus. Given that ER-SCRs can indicate the level of emotional stimulation and the extent to which participants are engaged in the activities, researchers usually focus on analyzing the ER-SCRs. According to [19], four main features can be extracted and analyzed regarding the ER-SCRs signals. Those are the following :

1) **Latency:** The period from the beginning of the stimulus to the beginning of the phasic burst.
2) **Peak Amplitude:** The difference between the peak and the level of the EDA signal at the beginning of the stimulus.
3) **Rise Time:** The time that is needed for the EDA signal to rise from the beginning of the signal until it reaches the peak.
4) **Recovery Time:** The needed time for the signal from peak to the initial measurement.

B. Wearable device

We use the Empatica E4, which is a wearable on-the-wrist device. Our aim is to use the device on a daily basis, while the individuals using it are free to go about their everyday lives. The experiments are not conducted in a controlled environment in order to have more realistic results. The E4 is equipped with a number of sensors, a PPG sensor that measures the HRV of the subject giving us insights regarding the emotional state of the person, a 3-axis accelerometer to detect the movement and the activity, a temperature sensor (optical thermometer) and an EDA sensor to monitor the emotional state of the person. The PPG and the temperature sensor of the device are located on the bottom side of the device, while the EDA electrodes are placed on the wristband [22]. The device will obtain data from sensors regarding the EDA activity of the individuals. The data received will be raw and thus will not have undergone any processing.

The sampling frequency of the E4 is at 4Hz and the variation ranges from 0.01 μSiemens to 100 μSiemens, with a peak value of 100 μSiemens. This measurement is performed using 2 silver (Ag) electrodes which are placed on the bracelet of the device. Other wearables that are widely used in the market, and in similar research, are Samsung Gear Sport smartwatches and FitBit smartwatches.

C. Cloud service

The data samples collected from the wearable device will be sent to a cloud application, where they will be processed. Comparing the metrics we get from the wearable with the analytics in terms of social media usage, we aim to find out if and how the use of social media content affects the emotional state of the individual. We examine if we can observe this from the EDA metrics in those hours when the user is active on social media.

IV. Methodology

There are three main components that the acquired signal should go through before any further analysis. The components are shown in Fig. 3 and are discussed below.

A. Data preprocessing

Before analyzing the data, preprocessing the data to remove noise and artifacts is essential [23], [24]. Common preprocessing steps include filtering, baseline correction, and artifact removal.

Filtering is used to remove unwanted noise from the signal. The choice of filter depends on the characteristics of the noise and the frequency content of the signal. The widely used filters include low-pass filters, high-pass filters, and band-pass filters. A low-pass filter allows low-frequency components to pass through while attenuating high-frequency noise. A high-pass filter removes low-frequency drift or baseline shifts to make higher-frequency components pass through. A band-pass filter ensures a specific frequency band of interest to pass through, attenuating both low and high frequencies outside the band. The cutoff frequencies for these filters should be carefully selected based on the expected frequency range of the EDA signal and the noise characteristics.

EDA signals often exhibit slow baseline shifts or drifts. Baseline correction aims to remove these gradual changes to focus on the phasic components of the signal. Polynomial fitting, moving average, and median filtering are the commonly used methods for baseline correction.

EDA signal data can be affected by various artifacts that need to be identified and removed. Artifacts may include

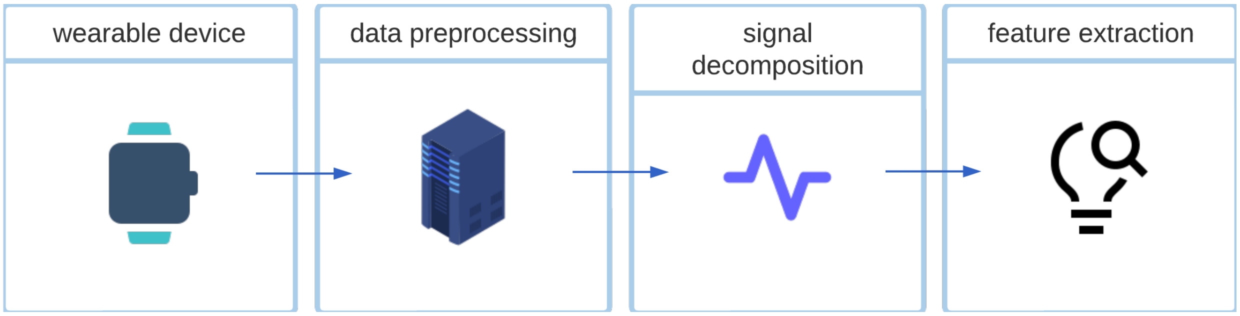


Fig. 3: Three main components that the acquired signal should go through before any further analysis.

sudden spikes, muscle movement artifacts, or other sources of interference. Some techniques for artifact removal include thresholding, wavelet denoising, and independent component analysis (ICA). Thresholding is to define a threshold value and remove data points that exceed the threshold, assuming they are artifacts. Wavelet denoising means applying wavelet transformation to the signal and removing high-frequency noise components while preserving the important features. ICA is used to separate the EDA signal from other sources of interference by decomposing the mixed signal into independent components.

In this study, the signals will be segmented with a 30-second non-overlapping window. The preprocessing methods that are applied to the segmented signals are a low-pass filter with a 3Hz cutoff frequency and a 4th-order Butterworth filter. Then, standardization is performed on the signal so that the data can be expressed in terms of standard deviation.

B. Signal decomposition

Signal decomposition is the procedure of separating a signal into its components or representations. This process involves converting the signal into an alternative representation that emphasizes particular aspects or characteristics of interest. For EDA signal, the decomposition process will separate the signal into Phasic and Tonic parts. The method used in this study is a high-pass filter with a cutoff frequency of 0.05Hz.

C. Feature extraction

Extracting meaningful features from the preprocessed signal is crucial for further analysis. In EDA signal, amplitude, frequency, and SCR are the prevalent features that are chosen. Especially, SCR can assist to identify and measure characteristics of specific skin conductance responses, such as onset latency, rise time, peak amplitude, and recovery time. In this study, the mean, standard deviation, minimum, and maximum value of the EDA signal, as well as the onset latency, rise time, peak amplitude, and recovery time from SCR will be extracted to form a vector for data analysis.

V. Experimental Results and Discussion

In the following, we present the data collection process followed by the preliminary results and the discussion.

A. Data collection

In the preliminary experiments, our goal is to examine the feasibility of identifying stress related to social media content. We used data collected from students from our University, during the Winter term. In the beginning, the students came to the lab and the basic functionality of Empatica E4 was presented to them. Then, they were instructed to wear the Empatica E4 at least for one day, on their left hand. During the day, the students were instructed to mention an event, while pressing the relevant button on Empatica, whenever they use social media and the content makes them have positive or negative feelings, while also reporting how they were feeling. The frequency with which users reported an event varied depending on how much they used social media on a daily basis. We tested the emotional response of the individuals while using popular social media apps such as Instagram, Facebook, Tik Tok and messaging apps like Facebook Messenger and Viber.

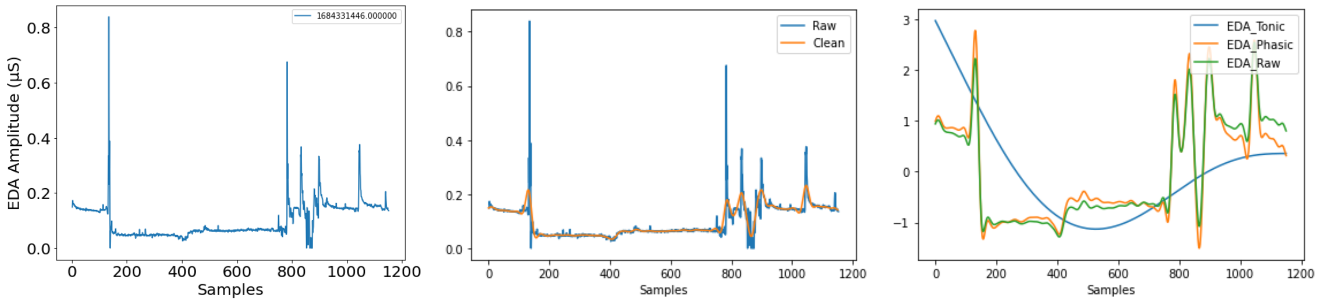
When the students returned the equipment, the data from their smartphones, regarding social media usage, along with the E4 data were collected for data labeling and classification. On average, the students provided data for seven days. We asked the participants to repeat the experiments after a week hoping that they would have different interactions with social media under varied conditions.

B. Preliminary data analysis

According to the preliminary data we have identified four main scenarios that are shown in Fig. 4-7, along with the raw data, the clean data, and the EDA components.

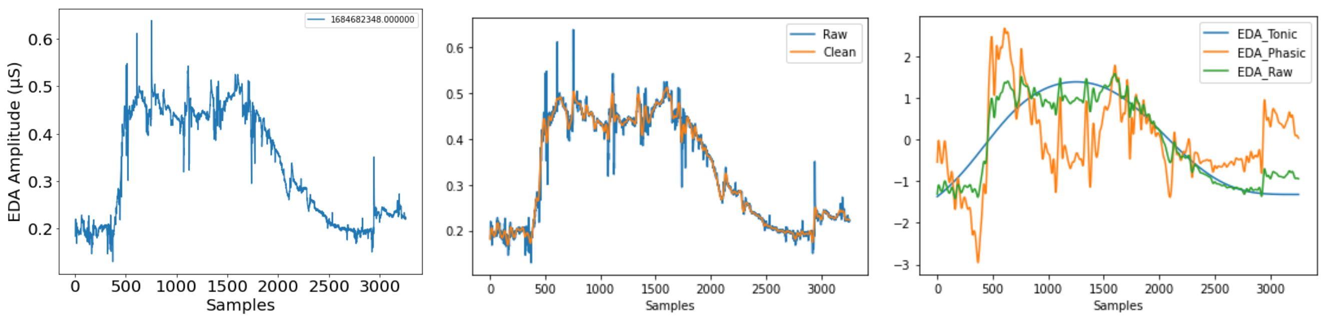
During the first scenario, shown in Fig. 4, we identify users who reported low social media usage over short periods of time per day. Low usage refers to the use of social media by an individual for an amount of time but with some interruptions. The interruptions may be due to the user being outdoors, socializing, watching TV etc., while using a social media app. According to the correlation analysis between the EDA levels and social media content, there is a correlation of 0.63 between the content and the stress level as reported by the users.

In the second scenario, shown in Fig. 5, the users had high social media usage over a short time. The term high usage refers to the use of social media by an individual without interruptions for an amount of time. The correlation analysis in this scenario shows again a positive correlation of 0.67



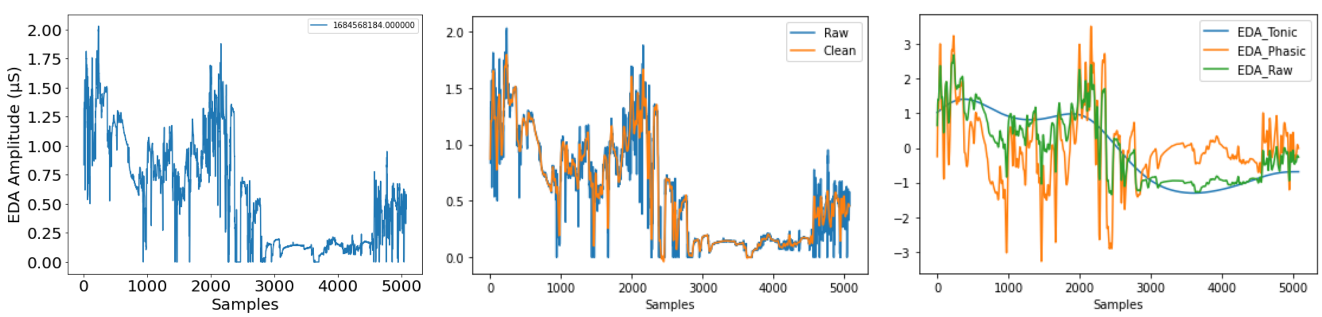
(a) Raw data (b) Raw and Clean data (c) EDA components

Fig. 4: Scenario 1 - Low Usage, Short Time: (a) Raw data (b) Raw and Clean data (c) EDA components.



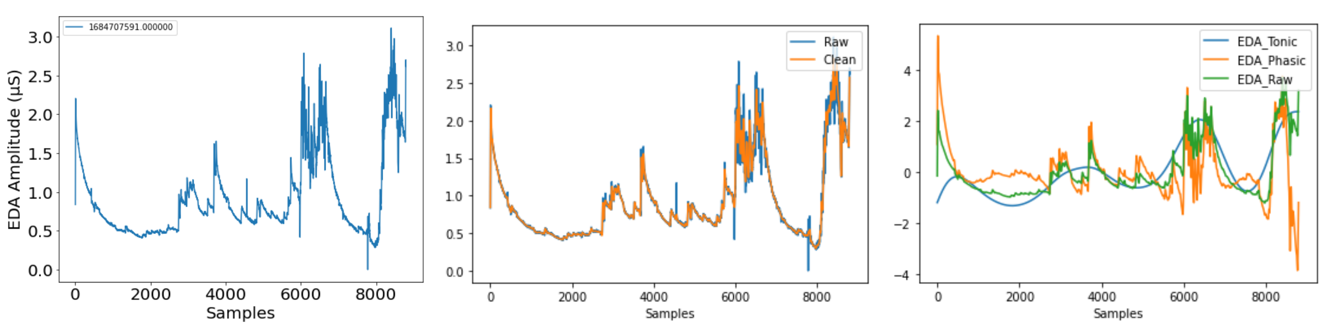
(a) Raw data (b) Raw and Clean data (c) EDA components

Fig. 5: Scenario 2 - High Usage, Short Time: (a) Raw data (b) Raw and Clean data (c) EDA components.



(a) Raw data (b) Raw and Clean data (c) EDA components

Fig. 6: Session 3 - Low Usage, Long Time (a) Raw data (b) Raw and Clean data (c) EDA components.



(a) Raw data (b) Raw and Clean data (c) EDA components

Fig. 7: Scenario 4 - High Usage, Long Time: (a) Raw data (b) Raw and Clean data (c) EDA components.

between the reported stress level and the content of social media.

In the third scenario, shown in Fig. 6, the users recorded data over longer periods during the day, however, they did not report social media usage often. Due to the longer period, the signals seem to have more noise, while the correlation is lower than before at 0.58.

In the fourth scenario, shown in Fig. 7, the users reported high usage of social media over a long time. Although this scenario suffered again from noise, the correlation was at 0.65.

C. Discussion

The preliminary data are promising regarding the correlation between the stress level and social media content. According to the experimental results, EDA has the potential to identify stress levels. When the user reported stress while interacting with social media content, especially in short social media usage, the proposed approach was able to properly identify it. Also, when the stress level was reported less often during the day, the proposed approach had better accuracy.

At the same time, there are some challenges. Further data labeling and classification are necessary. The motion artifacts that are included in the wrist-collected signals are hard to remove and their existence can create several challenges in proper stress level classification. Hence, more advanced signal processing approaches are necessary, especially for sessions with long data collection periods.

Overall, more users with different backgrounds and ages are needed. This could help to better support the preliminary claims and further explore the potential of the proposed approach under different usages.

VI. Conclusion

In this work, we examine the feasibility of stress detection related to social media content. We used EDA signals collected from wrist-based wearable devices and we examined the correlation between the content and the self-reported stress level. The experimental results showed the potential of EDA as an indicator for stress level detection while using social media. At the same time, they revealed important challenges such as proper signal processing and motion artifact removal for efficient prediction. The findings from this study are based on preliminary results, and further experiments are needed.

References

[1] U. Phalswal, V. Pujari, R. Sethi, and R. Verma, "Impact of social media on mental health of the general population during covid-19 pandemic: A systematic review," *Journal of Education and Health Promotion*, vol. 12, 2023.

[2] B. Dean, "Backlinko social network usage growth statistics: How many people use social media in 2023?," https://backlinko.com/social-media-users, 2023.

[3] H. Lin, J. Jia, J. Qiu, Y. Zhang, G. Shen, L. Xie, J. Tang, L. Feng, and T. Chua, "Detecting stress based on social interactions in social networks," *IEEE Transactions on Knowledge and Data Engineering*, vol. PP, pp. 1–1, 03 2017.

[4] G. Giannakakis, D. Grigoriadis, K. Giannakaki, O. Simantiraki, A. Roniotis, and M. Tsiknakis, "Review on psychological stress detection using biosignals," *IEEE Transactions on Affective Computing*, vol. 13, no. 1, pp. 440–460, 2022.

[5] S. Gedam and S. Paul, "A review on mental stress detection using wearable sensors and machine learning techniques," *IEEE Access*, vol. 9, pp. 84045–84066, 2021.

[6] N. Keshan, P. V. Parimi, and I. Bichindaritz, "Machine learning for stress detection from ecg signals in automobile drivers," in *2015 IEEE International Conference on Big Data (Big Data)*, 2015, pp. 2661–2669.

[7] L. Vanitha and G. R. Suresh, "Hybrid svm classification technique to detect mental stress in human beings using ecg signals," in *2013 International Conference on Advanced Computing and Communication Systems*, 2013, pp. 1–6.

[8] P. Mohan, V. Nagarajan, and S. Das, "Stress measurement from wearable photoplethysmographic sensor using heart rate variability data," in *2016 International Conference on Communication and Signal Processing (ICCSP)*, 2016, pp. 1141–1144.

[9] Y. Hasanpoor, K. Motaman, B. Tarvirdizadeh, K. Alipour, and M. Ghamari, "Stress detection using ppg signal and combined deep cnn-mlp network," in *2022 29th National and 7th International Iranian Conference on Biomedical Engineering (ICBME)*, 2022, pp. 223–228.

[10] S. Betti, R. Lova, E. Rovini, G. Acerbi, L. Santarelli, M. Cabiati, S. Ry, and F. Cavallo, "Evaluation of an integrated system of wearable physiological sensors for stress monitoring in working environments by using biological markers," *IEEE Transactions on Biomedical Engineering*, vol. 65, no. 8, pp. 1748–1758, 2018.

[11] P. Bobade and M. Vani, "Stress detection with machine learning and deep learning using multimodal physiological data," in *2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA)*, 2020, pp. 51–57.

[12] I. Moshe, Y. Terhorst, K. Opoku Asare, L. Sander, D. Ferreira, H. Baumeister, D. Mohr, and L. Pulkki-Råback, "Predicting symptoms of depression and anxiety using smartphone and wearable data," *Frontiers in Psychiatry*, vol. 12, 2021.

[13] C. Setz, B. Arnrich, J. Schumm, R. La Marca, G. Tröster, and U. Ehlert, "Discriminating stress from cognitive load using a wearable eda device," *IEEE Transactions on Information Technology in Biomedicine*, vol. 14, no. 2, pp. 410–417, 2010.

[14] J. Wijsman, B. Grundlehner, H. Liu, H. Hermens, and J. Penders, "Towards mental stress detection using wearable physiological sensors," pp. 1798–1801, 2011.

[15] M. Majeed, M. Irshad, T. Fatima, J. Khan, and M. Hassan, "Relationship between problematic social media usage and employee depression: A moderated mediation model of mindfulness and fear of covid-19," *Frontiers in Psychology*, vol. 11, 2020.

[16] M. Hammad and T. Alqarni, "Psychosocial effects of social media on the saudi society during the coronavirus disease 2019 pandemic: A cross-sectional study," *PLOS ONE*, vol. 16, pp. e0248811, 03 2021.

[17] A. Pirdehghan, E. Khezmeh, and S. Panahi, "Social media use and sleep disturbance among adolescents: A cross-sectional study," *Iranian Journal of Psychiatry*, vol. 16, no. 2, pp. 137–145, Apr. 2021.

[18] R. Alonzo, J. Hussain, S. Stranges, and K. Anderson, "Interplay between social media use, sleep quality, and mental health in youth: A systematic review," *Sleep medicine reviews*, vol. 56, pp. 101414, April 2021.

[19] L. Zhu, P. Spachos, P. Ng, Y. Yu, Y. Wang, K. Plataniotis, and D. Hatzinakos, "Stress detection through wrist-based electrodermal activity monitoring and machine learning," *IEEE Journal of Biomedical and Health Informatics*, vol. 27, no. 5, pp. 2155–2165, 2023.

[20] R. J. Narayan, *Encyclopedia of Sensors and Biosensors*, 2022.

[21] "Empatica what should i know to use eda data in my experiment?," https://support.empatica.com/hc/en-us/articles/203621955-What-should-I-know-to-use-EDA-data-in-my-experiment-, 2020.

[22] "Empatica E4 wristband user's manual document," https://support.empatica.com/hc/en-us/articles/202581999-E4-wristband-technical-specifications, 2020.

[23] A. Greco, G. Valenza, A. Lanata, E. Scilingo, and L. Citi, "cvxeda: A convex optimization approach to electrodermal activity processing," *IEEE Transactions on Biomedical Engineering*, vol. 63, no. 4, pp. 797–804, 2016.

[24] S. Taylor, N. Jaques, W. Chen, S. Fedor, A. Sano, and R. Picard, "Automatic identification of artifacts in electrodermal activity data," in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2015, pp. 1934–1937.