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Privacy Preserving Stress Detection System Using Physiological Data from Wearable Device

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ABSTRACT

Stress is considered to be an emotional state deserving of special attention, as it brings about harmful effects on human health when exposed to in the long term. Stress may also induce general health risks, including headaches, sleep disorders, and cardiovascular diseases. Continuous monitoring of emotion can help patients suffering from psychiatric disorders better understand themselves and promote the emotional well-being of the public in general. Recent advancements in wearable technologies and biosensors enable a decent level of emotion and stress detection through multimodal machine learning analysis and measurement outside of lab conditions. As machine learning solutions demand a large amount of training data, collecting and combining personal data is a prerequisite for accurate analysis. However, due to the highly sensitive nature of medical data, the additional implementation of measures for the preservation of user privacy is a non-trivial task when developing an AI-based stress detection solution. We propose a novel machine learning stress detection system that facilitates privacy-preserving data exploitation based on *FedAvg*, a renowned federated learning algorithm. We evaluated our system design on a standard multimodal dataset for the detection of stress. Experiment results demonstrate that our system may achieve a detection accuracy of 75% without jeopardizing the privacy of user data.

Keywords: Physiological sensors, Wearable, Federated learning, Artificial intelligence, Machine learning

INTRODUCTION

Emotion recognition is the act of recognizing and differentiating human affections. Detecting human emotion has a wide range of potential applications, especially in the domain of human-computer interfaces and healthcare. The implementation of affection detection in autonomous vehicles, human-robot interactions, video games, and recommendation systems are some of the most desired topics of research [Bota et al., 2019]. Continuous emotion monitoring has the potential to help patients suffering from psychiatric disorders, and to promote the emotional well-being of the public, resulting in improved quality of life for many, along with making the prevention of mental illness possible in the first place.

In healthcare applications, stress is considered a noticeable emotional state, as it harms human health when exposed to in the long-term. According to the British Health and Safety Executive (HSE), stress and emotional difficulties accounted for half of the cases of all work-related illnesses in the UK [Owen, 2022]. Stress can also lead to general health problems, such as headaches, sleep disorders, and cardiovascular diseases. It may also decrease the work efficiency of employees. An effective and automated stress detection method may prove to be an excellent way to mitigate these problems.

Stress is a physiological response to a stimulus triggered by the sympathetic nervous system (SNS). The response can differ depending on the subject and the measuring environment. Recent advancements in wearable technologies and biosensors enable decent stress detection through multimodal machine learning analysis and off-lab measurement. Different sensors, including photoplethysmography (PPG) sensors to measure blood volume pulse (BVP), thermometers to measure body temperature, and electrodermal activity (EDA) sensors to measure galvanic skin response may be loaded on wearable devices. Data collected from these devices may in turn be used to train artificial intelligence (AI) models for the detection of stress and emotion.

However, the application of AI in healthcare has certain challenges. Machine learning (ML), especially deep-learning (DL) solutions, demand a large amount of training data which may require a significant amount of time to collect. Also, due to the highly confidential nature of medical data, many privacy related regulations such as the General Data Protection Regulation (GDPR) are being actively introduced. While these legal protections are necessary, one cannot deny that they add on to the burden when developing AI solutions for medical applications.

Federated Learning (FL) is a learning paradigm that seeks to address the problem of data management and privacy by training algorithms collaboratively without exchanging the training data itself. FL involves the training of statistical models between remote devices or siloed data centers, such as mobile phones or hospitals, all without sharing data. Therefore, FL is able to address the problem of training data deficiency and privacy-preservation [Rieke et al., 2020, Li et al., 2020]. Due to its significant advantage, FL is proposed as an appropriate machine learning concept in the context of healthcare. In this work, we aim to propose a stress detection system based on the concept of federated learning.

RELATED WORKS

Physiological Data

Blood Volume Pulse (BVP) The blood volume pulse (BVP) signal is a measure of changes in blood volume in arteries and capillaries. It is measured by shining an infrared light through human tissues and detecting their reflections using PPG sensors. The BVP amplitude displays moment-by-moment heart rate variability (HRV) and may offer significant insight into individual emotional responses.

Electrodermal Activity (EDA) In the last few decades, electrodermal activity (EDA) has been one of the most popular physiological signals when

Table 1. Dataset distribution.

Class	# of samples
Amusement	195
Baseline	628
Stress	355

concerning affective computing and emotion recognition. The detection of changes in sweat gland activity for specific stimuli has allowed for the expansion of the frontier in affective computing by providing real time autonomous nervous system (ANS) activity monitoring. The EDA signal is mainly divided into two parts: phasic and tonic components.

Skin Temperature (TEMP) Simple, accurate measurements of skin surface temperature, particularly taken by wearable devices, are of growing interest given their physiological significance.

Respiration Rate (RESP) The respiration and heartbeat signals are affected by the emotional status of the subject. The mechanical activities of the heart muscles and lungs induce a vibration inside the chest wall. A piezoelectric cantilever placed on top of the chest surface is capable of collecting such vibrations and converting them into an electrical voltage signal.

Dataset

We employ the *WESAD* dataset [Schmidt et al., 2018] to evaluate the performance of our proposed system and compare the results. The *WESAD* dataset consists of raw data collected by the *RespiBAN Professional* (PLUX Wireless Biosignals S.A., Portugal) wearable respiration monitoring system and the *Empatica E4* (Empatica Inc., USA) wristband. This dataset features the physiological data of 15 subjects collected by the above devices, which are classified into three classes; Amusement, Baseline, and Stress. The labels were assigned using machine learning models, which were trained on sample data from different emotional states [Schmidt et al., 2018]. Tab. 1 describes the class distribution of the data in detail.

RespiBAN Professional The *RespiBAN Professional* is a chest-worn device capable of recording the electrocardiogram (ECG), EDA, electromyography (EMG), piezoelectric respiration (RESP), and TEMP data at sampling rates of up to 1000Hz [Bio, 2018]. All signals were sampled at a rate of 700Hz for the dataset. In this research, only RESP data was used for analysis.

Empatica E4 The *Empatica E4* is a wrist-worn device which is capable of recording acceleration (ACC), BVP, EDA, and TEMP. ACC data was sampled at a rate of 32Hz, BVP at 64Hz, EDA at 4Hz, and TEMP at 4Hz. All types of data measured using the *Empatica E4* were used in this research.

System Design

We propose a system that analyses physiological data collected from wearable devices to determine the emotional state of a given individual, aided by occasional user input via a dedicated mobile application, with an emphasis on privacy.

Data From Wearable Devices

As our current work is focused on the privacy-oriented nature of the proposed emotional state classification system, we will simulate the collection of data from wearable devices by utilizing the *WESAD* dataset; described in Section 2.2. In the future, we will advance the proposed system based on directly performed data collection using a smart watch that is fully integrated into our system.

Custom Mobile Application

We make use of a custom mobile application that is designed to periodically collect physiological data of choice from wearable devices. The mobile application performs the function of visualizing the various kinds of physiological data that was collected by the wearable device in use, and certain extra features that were derived from the initial set of raw data. Enabling user-aided emotion labelling and user interaction will be integrated to the application in the future. Fig. 1a demonstrates our custom mobile application.

Privacy Oriented Analysis

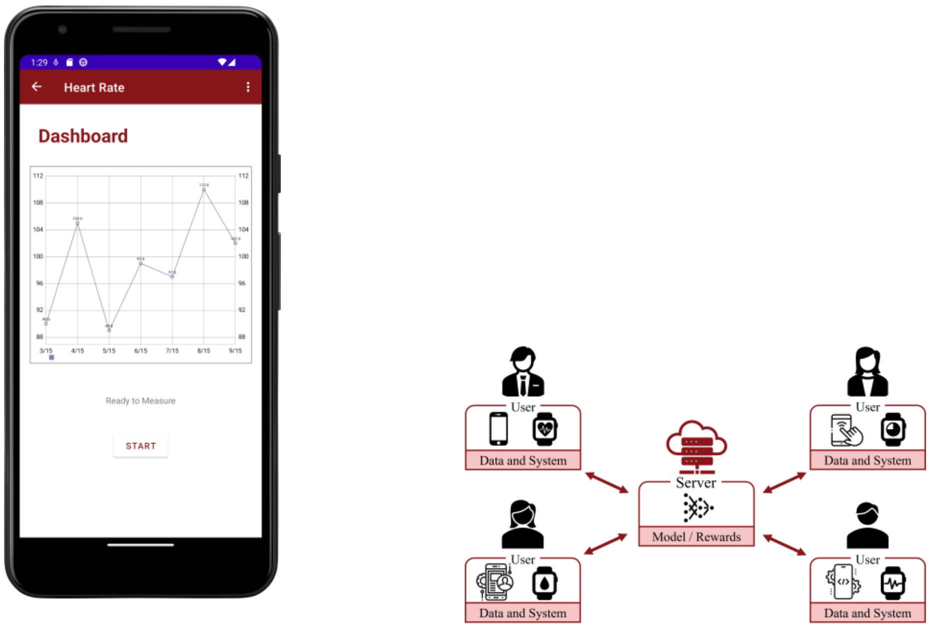
Given the inherently private and sensitive nature of personal health data, it could be said that maintaining the privacy of personal health data while using it for analysis is of great importance. We attempt to tackle this issue by using the *FedAvg* algorithm, a promising federated learning algorithm. By implementing federated learning in our model, we rule out the possibility of user privacy breach by ensuring that the central server never handles raw data collected from wearable devices, but only uses the weights generated from the user's device on premise. Fig. 1b illustrates the overall learning process of our system.

EXPERIMENT

We conduct experiments to evaluate our proposed system using *PyTorch* as the machine learning framework with Python as the programming language of choice. To accelerate the training process of the proposed machine learning model, we use one NVIDIA RTX 2080 SUPER GPU with 8GB of memory.

Pre-Processing

The raw data (BVP, RESP, TEMP) from sensors are processed and extracted into a form that can be employed in machine learning model training. The time series data is analyzed with a window frame of 30 seconds as a data point. We calculate the mean, standard deviation, minimum value, and maximum value for each window frame. On EDA data, we applied the cvxEDA algorithm [Greco et al., 2015], which decomposes the measurement into the tonic, phasic, and additive noise term using the convex optimization. The components reflect changes in skin such as changes in skin conductivity and



(a) Custom Mobile Application (b) Privacy-oriented learning

Figure 1: Sample human systems integration test parameters (Folds et al. 2008)..

Table 2. Complete list of features.

Type of data	Features
BVP	BVP-mean, BVP-std, BVP-min, BVP-max, BVP-peak-freq
EDA phasic	EDA-phasic-mean, EDA-phasic-std, EDA-phasic-min, EDA-phasic-max
EDA smna	EDA-smna-mean, EDA-smna-std, EDA-smna-min, EDA-smna-max
EDA tonic	EDA-tonic-mean, EDA-tonic-std, EDA-tonic-min, EDA-tonic-max
Respiration rate	Resp-mean, Resp-std, Resp-min, Resp-max
Body temperature	TEMP-mean, TEMP-std, TEMP-min, TEMP-max, TEMP-slope
Personal measurement	Age, Height, Weight

the sweat glands, thus enabling stress detection. We also calculated statistical values for the three types of data, respectively.

Tab. 1 shows the number of samples for each class we can extract from 15 subjects in the *WESAD* dataset. Also, the complete list of 29 features extracted from sensor data and personal measurement is shown in Tab. 2.

Training Procedure

We simulate the training process with 14 clients on our custom designed federated learning framework. The server first broadcasts a neural network model (Fig. 2 with all parameters initialized to zero. Each client owns the data from one subject from the *WESAD* dataset. The clients train the received model using the local data and send the model parameter values back to the server. The server aggregates the model weights from all the clients using the canonical *FedAvg* algorithm [McMahan et al., 2017]. The aggregated model is

Figure 2: Neural Network Architecture.

Table 3. Accuracy comparison between centralized training and the proposed federated learning approach.

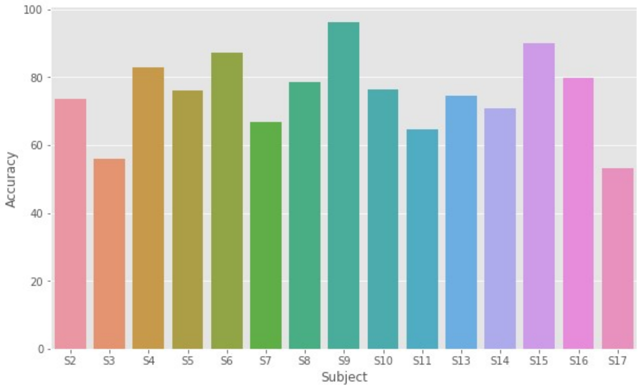
Subject	Centralized	Federated (Proposed)
S2	76%	73%
S3	66%	55%
S4	83%	82%
S5	42%	75%
S6	81%	87%
S7	69%	66%
S8	78%	78%
S9	99%	96%
S10	74%	76%
S11	78%	64%
S13	73%	74%
S14	77%	70%
S15	92%	89%
S16	72%	79%
S17	62%	53%
Mean	74.8%	75.0%

evaluated at the server on unseen test data and is broadcasted back to the clients for further training. The entire process continues until the aggregate model converges.

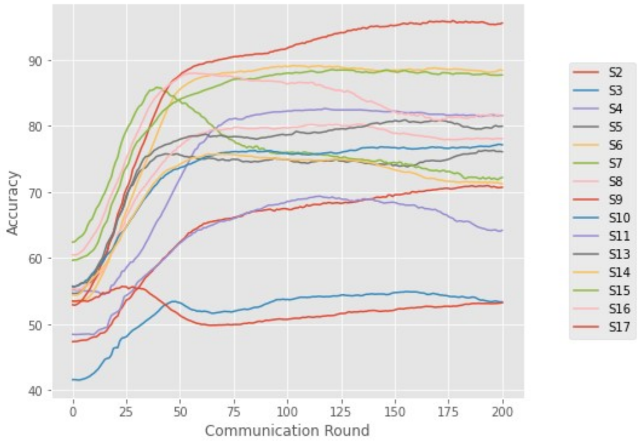
The entire process mimics the scenarios in which multiple users separately train the machine learning model on their personal data and contribute to the global model by providing only the trained model weights, thus not exposing the private data. We simulate the training process 14 times; each training includes 200 communication rounds, resulting in a fixed learning rate of 0.005.

EVALUATION

The proposed federated learning stress detection system is simulated with 14 clients; each client is assigned to a single subject data from the *WESAD* dataset. Data of one subject is reserved as the unseen test data to evaluate the aggregated model after each round. This method is similar to the Leave One Out Cross Validation (LOOCV) method, which is also a widely used method for evaluating machine learning models. For comparison, we conduct traditional centralized training; data from 14 subjects are used to train one model, and the remaining subject data is used for evaluation. The training hyperparameters are kept constant during both federated learning and centralized learning. The accuracy values of the two methods are presented in Tab. 3 for comparison.



(a) Accuracy of each subject for unseen test data



(b) Accuracy over communication round

Figure 3: Evaluation results.

Overall, our proposed system shows an equal level of performance in comparison to the traditional centralized system, where the users must agree to share their data with the server to train a single model on a central server. The accuracy of each method is evaluated with the unseen test data, which is presented in Fig. 3a. We can observe that the physiological data of the stressed state varies vastly according to each person. Thus personalization of the machine learning model is crucial in the stress detection system and will be considered in future research to enhance performance.

Lastly, the accuracy of the aggregated model over each communication round is presented in Fig. 3b. The plot shows that the aggregated model converges after 100 communication rounds, thus achieving the best accuracy possible at that stage. Nevertheless, as the volume of training data increases over time, increasing the number of communication rounds is necessary to guarantee that the aggregated model converges to its global optimum.

CONCLUSION

Physiological data from sensors embedded in wearable devices combined with artificial intelligence facilitates the detection of stress and emotion, which brings benefits not only to patients with psychiatric disorders, but also to the general population. We proposed a stress detection system based on federated learning to help preserve the privacy of user data while engaging in analytic activities concerning user stress and emotional state. We demonstrated that our design could achieve the same performance with traditional centralized system designs. In the future, we plan to improve the strategy for updating the detection model with newly collected data over time as well as enhancing the robustness of the system to cope with heterogeneous data from malfunctioning sensors and user dropouts.

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