YSUY: Your Smartphone Understands You – Using Machine Learning to Address Fundamental Human Needs

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Abstract—Most machine learning (ML) models are geared towards improving some desired metric like classification accuracy or inference latency. Given the significant successes of such models, especially supervised ones, in addressing such metrics, the time has come to ask if they can also be put to direct use in understanding the users and addressing basic human needs, e.g., subsistence, protection, affection, understanding, participation, leisure, creation, identity, and freedom. A prerequisite to addressing such human needs is that the ML models exhibit a basic grasp of human psychology. In this paper, we present ML models that can be embedded in our smartphone and enable it to understand us. We call this system "your smartphone understands you (YSUY)." YSUY uses wearable medical sensors to understand our physical, mental, and 4-class (2-class) emotional states with 91.2%, 91.1%, and 96.9% (99.1%) accuracy, respectively. After verifying YSUY's ability to understand the human condition from various perspectives, we evaluate the relationship between the different states and discuss how YSUY can be taken one step further to start playing a helpful role in addressing human needs of the types mentioned above from four different perspectives: 'being,' 'doing,' 'having,' and 'interacting.' We show that YSUY is a promising candidate for adapting ML models to human-centric needs. We view this only as an initial step, hopefully, spurring other researchers to investigate the relationship between ML models and fulfilling human needs in much greater depth.

Index Terms—Affection, classification, creation, emotional state, freedom, human needs, inference, identity, Internet-of-Things, leisure, machine learning, mental state, physical activity, participation, physical state, protection, smartness, smartphone, subsistence, wearable medical sensors.

1 Introduction

Artificial intelligence (AI) technologies have begun to have an impact on a wide range of application areas, such as natural language processing, healthcare, transportation, entertainment, education, safety, and security, thus enhancing the quality of life of their users. Owing to their success in being able to tackle complex tasks, these technologies are experiencing rapid growth. According to a report by McKinsey & Co., AI is expected to have a \$3.5T to \$5.8T impact on the global economy across 19 industries and nine business functions [1]. As AI makes greater inroads into our day-to-day lives, human-AI interactions become an important aspect to consider. These interactions are expected to become stronger and more personalized [2].

Currently, it is up to the users to assess their human needs and think of how AI technologies can be used to address those needs. This places the burden on the users to assess the needs in an accurate and timely fashion. According to Garry Kasparov, the chess grandmaster, humans spend approximately 99% of their resources for understanding and the remaining for computation; however, AI technologies do the opposite: they utilize 99% of their resources for computation and the remaining for understanding [3]. While these percentages can be debated, the complementary emphasis on understanding and computation seems to be true. Due to this difference, current AI technologies need to depend on the users for decision-making. Once the users make a decision regarding which task should be executed next, the corresponding AI technologies execute it with high accuracy and efficiency. Since AI technologies do not focus on understanding the users, they require the users to assess the situation and their needs. This leads to a gap between the users and the technology; therefore, it weakens the human-AI interaction.

In order to close this gap and enhance the incorporation and effectiveness of AI technologies, we propose an ML-based system: YSUY. YSUY uses wearable medical sensors (WMSs), typically present in small form-factor devices, such as a smartwatch or smartphone, to gauge the physical, mental, and emotional states of the users. After performing an extensive analysis of YSUY, we provide a detailed discussion of how it can be used to begin to address various human needs. Max-Neef presents an elegant 36-cell matrix that delineates nine human needs in four dimensions [4]. We discuss how these cells can be addressed by YSUY.

The main contributions of this paper are as follows:

- We present an ML-based system, YSUY, that attempts to understand the physical, mental, and emotional states of the users and their needs. YSUY serves as a bridge between the human and the AI technology.
- We advocate the need for understanding to flow from AI technologies, such as ML models, towards human needs so that these needs can be more efficiently addressed.

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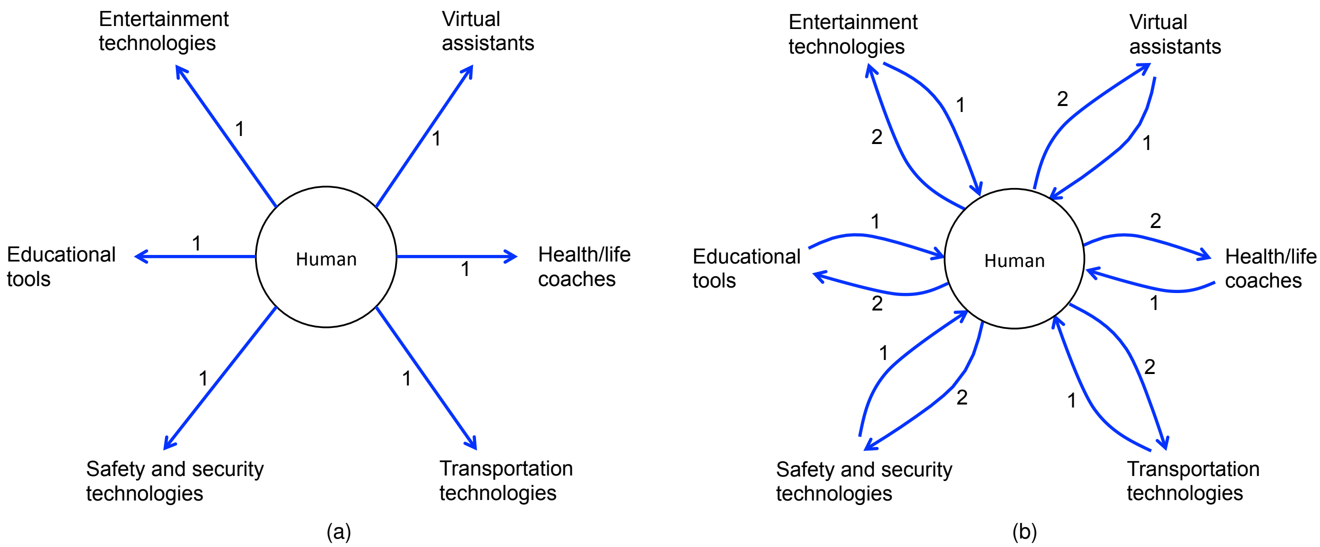


Fig. 1. Operational flow diagram of (a) traditional smart Internet-of-Things (IoT) and (b) YSUY technologies. The numbers indicate the order of operations.

- We describe a smartphone app for YSUY and perform experiments with it in real-life situations, without limiting the users to specific experimental protocols.
- We provide detailed classification analyses of the physical, mental, and emotional states and discuss the role YSUY can play by providing the state information in the context of four dimensions (i.e., 'being,' 'doing,' 'having,' and 'interacting.') of Max-Neef's fundamental human needs matrix.

The remainder of this paper is organized as follows. Section 2 provides the motivation behind developing a system that is focused on understanding the physical, mental, and emotional states of the users in real-time. Section 3 provides background information on fundamental human needs, ML-based technologies aimed at enhancing the quality of life of the users, and supervised ML algorithms. Section 4 introduces the methodologies for data collection, experimental flow, data processing, and feature extraction. Section 5 provides experimental results and a discussion on physical, mental, and emotional state detection. Section 6 analyzes the proposed system from the fundamental human needs perspective. Section 7 compares YSUY with previous physical, mental, and emotional-state related studies. Finally, Section 8 provides the future research directions and concludes the paper.

2 Motivation

ML applications accelerate, regulate, and enhance various processes we humans are interested in optimizing. Although significant progress has been made in developing such applications, the aim has mostly been to provide the highest accuracy and efficiency. Understanding the users and environmental factors has largely been missing from these endeavors. This situation is best summed up as follows: "... AI is a machine that can make a perfect chess move while the room is on fire" [58]. In order to take the AI technologies one step further and build on their already-formidable successes, the task-oriented approach needs to be augmented with a human-centered one. In other words, it is important for such technologies to understand human needs before performing the assigned task. YSUY is an approach that begins to address this problem.

Fig. 1a and 1b show the traditional and YSUY operational flow for ML technologies, respectively. In both these flows, the human is at the center and surrounded by various ML-based systems/tools/applications, namely entertainment technologies, virtual assistants, health/life coaches, transportation technologies, safety and security technologies, and educational tools. Arrows depict the operational flow. In the traditional approach, the users determine what their needs are and make use of the corresponding ML technology. The ML technology, upon receiving the command from the users, performs the task as requested. Therefore, the traditional approach requires the users to take some action. Since the commands come from the users, the arrows depicting the operational flow start from the users and end at the corresponding application. However, the YSUY approach first focuses on understanding the users. Therefore, arrow 1 is drawn from the applications to the human. The corresponding ML technology then carries out the assigned task, depicted by arrow 2. In this paper, we implement arrow 1 with three (i.e., physical, mental, and emotional) state assessment mechanisms, analyze its performance, and discuss its potential to understand the nine basic human needs: subsistence, protection, affection, understanding, participation, leisure, creation, identity, and freedom [4].

YSUY begins by collecting data through WMSs and the smartphone. Then, it processes the data, extracts features, and carries out classification to determine the state of the users from three different perspectives: physical, mental, and emotional. The states at a given time instance indicate whether the human need is being met. For example, in the case of subsistence, if the hunger need is not satisfied, then

TABLE 1
Human-Centered Machine Learning Applications

ML Area	Applications
Education	Smart classrooms [5], Virtual courses [6], Smart courses/tutoring [7], [8], [9], Automated feedback/grading [10], [11], Engagement assessment tools [12], [13], Simulations [14], [15]
Entertainment	Social media [16], [17], [18], Augmented reality (AR)/Virtual reality (VR) glasses/headsets [19], [20] AI-based images/movies/films/music [21], [22]
Healthcare	Fitness trackers [23], Fall detectors [24], [25], Sleep trackers [26], [27], Rehabilitation trackers [28], [29], Stress assistants [30], Location trackers [31], Posture detectors [32], Hydration monitors [33], [34], Insulin/Blood glucose level trackers [35], [36], Epileptic seizure monitors [37], [38], Emotion recognition [39], [40] Hearing aids [41], Overall wellness trackers [42]
Safety and security	Surveillance cameras/video systems/drones [43], Malware/spam detection and risk assessment tools [44], [45] Security automation/orchestration platforms/tools [46]
Transportation	Smart cars/vans/trucks [47], [48] Flying vehicles [49], Smart ships/marines [50], [51], Smart roads/highways [52], [53]
Virtual assistance	Apple's Siri [54], Amazon's Echo and Alexa [55], Google's Google Assistant [56], Microsoft's Cortana [57]

the 'hungry' label for the mental state points to this problem. The emotional state at that time instance may provide the reason, such as stress [59]. Similarly, the physical state at that time instance may provide a physical reason: perhaps, the user has been running, leading to pangs of hunger, or deliberately exercising appetite control to realize weight loss or deal with diabetes [60].

3 Background

In this section, we describe the basic human needs in detail. Then we explain how ML applications can address these needs.

3.1 Basic Human Needs

Determining what constitutes a realistic set of basic human needs and the relationships among them has been the focus of researchers for a long time. In 1938, Murray introduced a list of primary and secondary human needs and arranged them in a hierarchy [61]. He pointed out that the secondary needs (e.g., acquisition, dominance, autonomy, nurturance, etc.) stem from the primary needs (e.g., air, water, food, etc.). Maslow then introduced a five-layered pyramid model (physiological, safety, love and belonging, esteem, and self-actualization). Maslow's model was also hierarchical [62]. Then, by combining some of the layers in Maslow's model, Alderfer placed human needs into three categories: existence, relatedness, and growth [63], [64]. Similar to Alderfer, McClelland also grouped human needs in three classes: achievement, affiliation, and power, which do not depend on demographics [65].

Differently from the above models, Max-Neef introduced nine basic human needs (subsistence, protection, affection, understanding, participation, leisure, creation, identity, and freedom) viewed from four different perspectives ('being,' 'doing,' 'having,' and 'interacting') and placed them in a 36-cell matrix [4]. He eschewed hierarchy and acknowledged that the needs may be satisfied in different ways based on time, location, and situation. In other words, his human needs model is independent of cultural variations and time periods. However, the mechanisms for satisfying the corresponding needs may change over time, culture, and economical/political circumstances. This makes it a suitable model for YSUY to pursue. Moreover, according to Max-Neef's model, if one of the needs is not satisfied, deprivation occurs, placing a barrier to satisfying the remaining needs.

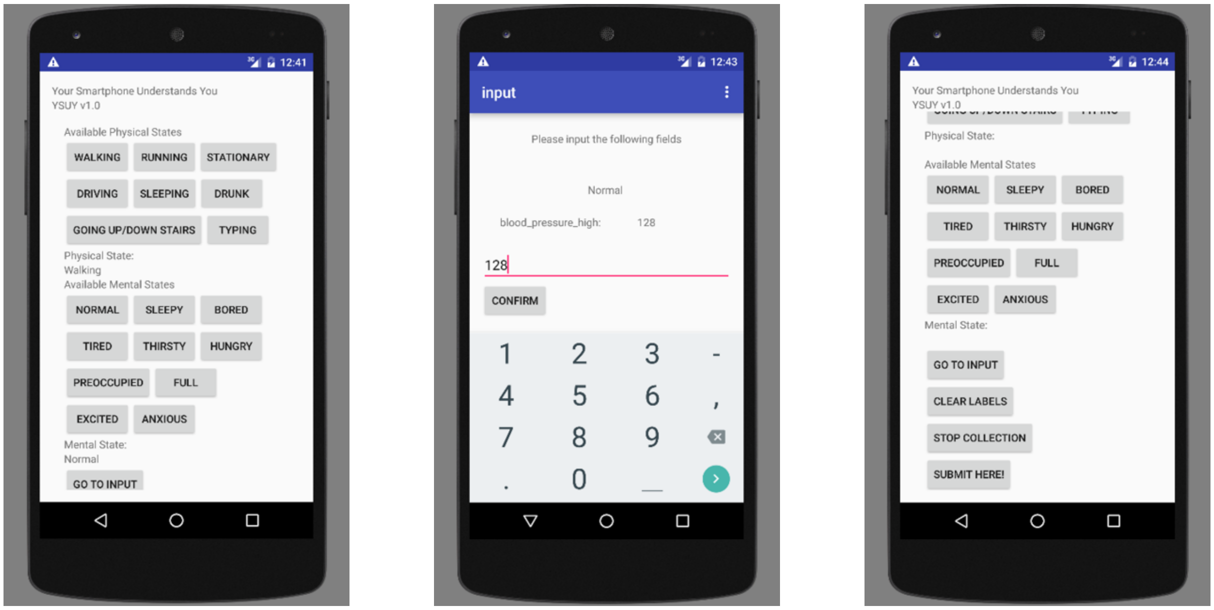
3.2 ML Applications

YSUY targets human-centered ML applications, which have begun to have an impact on a wide range of areas, as shown in Table. 1. We briefly describe these applications and how assessing the physical, mental, and emotional states of the user could improve them next.

The aim of educational tools is to enhance the quality of learning by targeting both the student and teacher sides. If the teacher understood the frustrations of the students, as manifested by their emotional state, he/she could provide a better and personalized learning experience for the students. Entertainment technologies range from social media to virtual reality tools. Understanding user needs and states could help personalize and optimize search to enhance user experience. Healthcare technologies promote quality of life of the users by detecting irregularities in physiological signals, thereby assisting in treatment or rehabilitation, and informing doctors or previously-assigned recipients about the user's health condition. If such systems understood the users better (psychology, needs, etc.), they could improve the user's quality of life further, by becoming human-centered rather than being task-centered. Safety and security technologies aim at monitoring tools, irregularity/risk assessment mechanisms/software, and automation systems. Being aware of the various user states may enhance responsiveness of these technologies. Transportation technologies also benefit from understanding the human as they focus on automating operations and providing safe, energy-efficient, and low-cost land/air/water transportation. With current virtual assistants (VAs), the users need to assess their own needs and then ask the VA to address them. However, if the VA understood the psychology of the users and was aware of their states (physical, mental, and emotional), it could deliver a higher level of performance, e.g., by performing complex, multi-staged, and parallel tasks [66].

3.3 Supervised ML Algorithms

Supervised ML algorithms classify an unlabeled data instance after having been trained with a set of data-label pairs. Multi-layer perceptron (MLP) is one of the high-performing ML algorithms. It is a fully-connected neural network that has an input and output layer and one or more hidden layers in between. It uses weights and activation functions in each layer to compute the corresponding labels. Its weights are trained by minimizing a loss function.



(a) (b) (c)

Fig. 2. User interface of the YSUY app: (a) upper part of the main menu, (b) data login section, and (c) lower part of the main menu.

Support vector machine (SVM) is another popular ML algorithm. It finds the separating hyperplane between classes, while maximizing the margin. If the classes are not linearly separable, then kernels, such as radial basis function (RBF), are used to project the data to a higher dimension where the classes become separable. k-nearest neighbors (kNN) is also a commonly used ML algorithm. It assigns the labels by carrying out a majority vote among the k nearest data instances.

4 METHODOLOGY

In this section, we describe the data collection, experimental flow, data processing, and feature extraction phases of YSUY.

4.1 Data Collection

YSUY bases its analyses of human states on data obtained from various angles by utilizing multiple sensors. It collects physiological [respiration, Galvanic skin response (GSR), blood volume pulse (BVP), skin temperature, blood pressure, and blood oxygen level] and electromechanical (three-axis accelerometer and gyroscope) signals through WMSs and a smartphone. The respiration sensor [67] and GSR [68] have a sampling rate of 10 Hz. The BVP and temperature sensors [69] have a sampling rate of 64 Hz and 4 Hz, respectively. The wearable accelerometer sensor [69] has a sampling rate of 32 Hz. An Android API for the smartphone [70] has a delay of 200 ms (corresponding to a maximum sampling rate of $5Hz$) and the smartphone's status affects this delay. Therefore, the sampling rate of the smartphone based data varies between 4 Hz and 5 Hz. In order not to distract the participant, we only collect blood pressure and blood oxygen levels once in each session.

A YSUY app is used to collect the physical state, mental state, blood pressure, and blood oxygen level information. The user interface of the app is shown in Fig. 2 (see Section 4.2 for details).

We collected data from seven participants (two females and five males: ages between 21 and 27) for the physical and mental state experiments and 11 participants (four females and seven males: ages 18 to 27) for the emotional state experiments. The experimental flow, content, smartphone app, and the consent form were approved by the Institutional Review Board of Princeton University. Before collecting the data, all participants were clearly informed about the experiment and they all signed a consent form. None of the participants reported any physical or mental disorder or any kind of health condition that would require continuous treatment or use of medication. The data obtained from one of the participants were not used for emotional state analyses due to the low quality of the acquired physiological signals.

4.2 Experimental Flow

We obtain data from the participants for the YSUY experiments for analyzing their three states (physical, mental, and emotional). The participants take part in the physical and mental state experiments while performing their daily activities in their own environments, without being limited to specific experimental protocols. For the emotional state experiments, we carry out a separate experimental flow to avoid biased results as the participant's emotional status reports can be affected by the participant's characteristic and environmental factors [71]. We explain the experimental procedures for obtaining the physical, mental, and emotional states in detail next.

4.2.1 *Physical and Mental State Experiments*

In the physical and mental state experiments, the WMSs (blood pressure monitor, blood oximeter, GSR sensor, respiration rate monitor, and a wristband that includes BVP, skin temperature, and accelerometer sensors), smartphone, and YSUY app (Fig. 2) are used. Data are collected while the participants experience daily life and fulfill their responsibilities in real-life situations. We aim at capturing the natural response of the participant and minimizing distractions by not specifying the frequency and duration of the session. Also, we do not ask the participants to undergo all possible physical and mental state options presented in the YSUY menu (Fig. 2a and Fig. 2c). We carry out the physical and mental state experiments with the following steps:

1) The participants wear the wristband. The wristband continuously collects data without requiring any intervention.
2) The participants describe their physical and mental states through the YSUY app. From this app, the participants select either one or multiple states from the given options (Fig. 2a and Fig. 2c)
3) The participants submit the blood pressure and blood oxygen level information at that time instant (Fig. 2b). Data collection starts.
4) Data collection continues until the participants stop the session through the YSUY app (Fig. 2c).

During the experiments, the participants provide their physical and mental state information. Although the total number of data logins for the two states are equal, the total number of different states might not be the same. For example, in the first data collection session, let us assume that the participant is in the 'walking' physical state and 'hungry' mental state, and in the second session, the participant is in the 'running' and 'hungry' physical and mental states, respectively. Overall, the participant has two data logins, but two different physical state reports and one mental state report.

4.2.2 Emotional State Experiments

In the emotional state experiments, we follow an experimental procedure that avoids biased reports. While distinguishing between the 'walking' and 'sleeping' physical states is straightforward for the participants, the emotional status reports can be affected by their characteristics and environmental factors [71]. In order to get around this problem, we stimulate the participants with pictures from the International Affective Picture System (IAPS) database [72]. This database includes pictures and their corresponding arousal-valence ratings that are validated through detailed experiments and analyses. As shown in the two-dimensional emotion chart (Fig. 3), each arousal and valence combination points to a particular emotion [73]. In order not to distract the participant and avoid situations that may affect the reporting of emotions, for each IAPS picture, we do not ask the users about their emotions, but use the arousal-valence ratings associated with the picture. We focus on four regions in the emotion chart: high arousal-high valence, low arousal-high valence, low arousal-low valence, and high arousal-low valence, corresponding to Quadrants I, II, III, and IV in Fig. 3, respectively. Moreover, using the ratings for females and males in the IAPS report [72], we select 80 pictures for each quadrant, as shown in Table 2. Then, to take the stochastic nature of real-life situations into account, we randomly choose 20 pictures from each quadrant for each participant. The flow of the emotional state experiment (Fig. 4) is as follows:

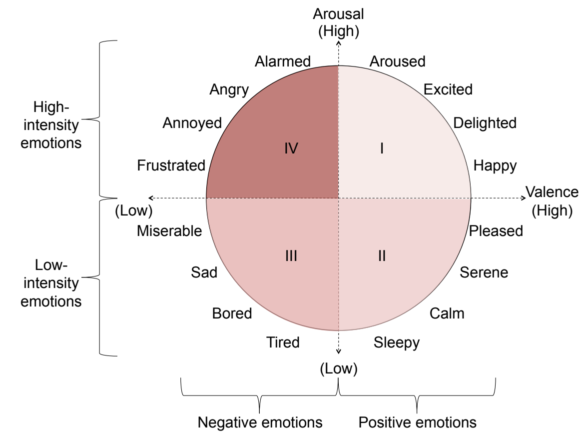


Fig. 3. Two-dimensional emotion chart.

1) We start the experiment by welcoming the participant, explaining the experiment, and placing the WMSs (blood pressure monitor, blood oximeter, GSR sensor, respiration rate monitor, and a wristband that includes BVP, skin temperature, and accelerometer sensors).
2) We display 20 pictures from each quadrant of the emotion chart. We show each IAPS picture for 30 s, leading to a 10-min session duration, as shown in red color in Fig. 4.
3) Since the pictures from different quadrants stimulate different emotions in the participants, in line with the experimental procedure described in [30], we give breaks in between the sessions to enable the participant to recover. During the breaks, we ask the participant to close their eyes and relax.
4) We end the experiment by taking out the WMSs and thanking the participant.

4.3 Data Processing and Feature Extraction

The data processing and feature extraction stages depend on the available data. Hence, the set of sensors used in the physical and mental state experiments is different than the set used for the emotional state experiments. We explain how YSUY processes the collected data for the two sets of experiments next.

4.3.1 Physical and Mental State

YSUY obtains data from two sources: WMSs and smartphone. The participant starts and ends data collection through the YSUY app while wearing the sensors. WMSs collect data continuously; however, inputs from the participant through the YSUY app determine the start time, end time, and labels (physical state and mental state) in the corresponding epoch. As the data are obtained from both the WMSs and smartphone, they need to be aligned in time. We primarily perform data aligment before further data processing and feature extraction, as shown in Fig. 5. The data alignment stage intersects the available WMS and smartphone data. It finds the start time (t_start) and end

TABLE 2
IAPS Database Picture Numbers for Female and Male Participants

Gender	High Arousal - High Valence	Low Arousal - High Valence	Low Arousal - Low Valence	High Arousal - Low Valence
Female	1340,1463,1710,1722,1811,1999,2045,2050,2058,2071,2075,2150,2155,2158,2160,2165,2208,2209,2216,2224,2300,2344,2345,2347,2352,2352.1,2550,4532,4542,4572,4575,4599,4610,4614,4623,4624,4626,4628,4640,4641,5260,5270,5460,5470,5480,5623,5700,5825,5833,5910,7230,7260,7270,7282,7330,7400,7405,7502,8033,8041,8080,8090,8162,8170,8190,8200,8210,8350,8380,8420,8460,8470,8496,8499,8500,8501,8502,8503,8531,8540	2095,2345.1,2375.1,2703,2751,2800,2900,3001,3005.1,3015,3016,3053,3059,3061,3062,3063,3064,3068,3069,3100,3101,3102,3103,3110,3130,3131,3140,3168,3170,3180,3181,3191,3195,3225,3230,3261,3266,3301,3350,3530,6021,6022,6315,6415,6563,9040,9075,9140,9181,9183,9185,9187,9252,9253,9254,9300,9301,9302,9322,9325,9326,9332,9405,9410,9412,9420,9421,9432,9433,9435,9570,9571,9635.1,9800,9902,9903,9910,9911,9921,9940	1505,2205,2278,2301,2312,2399,2455,2490,2525,2590,2682,2695,2700,2715,2716,2718,2722,2750,2752,2753,2795,2900.1,3190,3300,4001,4142,4210,4230,4235,4290,4300,4302,4635,6000,6010,6241,6800,7023,7079,7092,7136,7137,7520,7521,9000,9001,9002,9008,9041,9045,9046,9080,9101,9171,9180,9190,9220,9265,9270,9280,9290,9291,9330,9331,9341,9342,9390,9395,9404,9440,9445,9469,9471,9635.2,9830,9831,9832,9912,9913,9926	1440,1441,1460,1500,1540,1600,1620,1630,1721,1731,1750,1920,2035,2040,2057,2070,2080,2091,2151,2154,2156,2170,2222,2250,2260,2274,2299,2304,2306,2310,2311,2314,2331,2332,2340,2341,2360,2387,2388,2395,2398,2530,2540,2598,2630,2650,2660,4574,4616,4622,5001,5199,5201,5202,5210,5551,5594,5600,5660,5760,5779,5780,5811,5820,5829,5830,5831,5836,5982,7200,7280,7325,7470,7492,7570,7580,8032,8120,8461,8497
Male	1710,1811,2030,2152,2160,2209,2216,2340,2346,2391,4006,4008,4130,4141,4150,4180,4240,4250,4255,4275,4279,4310,4320,4599,4601,4607,4608,4626,4641,4650,4652,4653,4660,4670,4680,4690,5260,5270,5450,5460,5470,5480,5600,5623,5660,5700,5825,5833,5910,5982,7230,7270,7350,7405,7460,7480,7492,7502,7508,7580,8080,8116,8120,8170,8180,8190,8210,8300,8340,8370,8371,8380,8420,8470,8499,8501,8502,8503,8510,8531	2345.1,2352.2,2703,3001,3005.1,3015,3016,3030,3051,3053,3059,3060,3061,3062,3063,3064,3069,3071,3080,3100,3101,3102,3103,3110,3120,3130,3131,3140,3150,3160,3168,3170,3180,3191,3215,3220,3225,3261,3266,3350,3530,6021,6022,6212,6360,6520,6560,6570,7380,9006,9040,9075,9180,9183,9252,9253,9254,9322,9325,9326,9405,9410,9412,9413,9414,9419,9428,9520,9560,9570,9635.1,9800,9810,9901,9903,9904,9910,9911,9920,9921	1111,1275,2053,2055.1,2095,2120,2141,2205,2276,2278,2301,2375.1,2455,2456,2457,2590,2700,2750,2751,2799,2800,2900,2900.1,3017,3181,3300,3301,4621,6311,6561,7079,7135,7361,9000,9002,9007,9010,9031,9041,9043,9090,9102,9140,9145,9181,9182,9185,9220,9265,9280,9290,9295,9301,9302,9320,9330,9331,9340,9341,9342,9395,9415,9417,9421,9430,9432,9435,9452,9470,9471,9530,9561,9571,9584,9596,9610,9830,9831,9832,9912	1410,1440,1441,1460,1463,1500,1510,1540,1600,1660,1721,1722,1731,1740,1750,1920,1999,2040,2045,2050,2057,2058,2070,2071,2080,2091,2150,2153,2154,2158,2170,2208,2224,2260,2306,2311,2332,2345,2347,2352,2352.1,2373,2530,2540,2550,2650,2660,4603,5210,5220,5300,5594,5611,5631,5725,5760,5780,5781,5814,5820,5829,5830,5831,5836,7200,7250,7260,7280,7330,7390,7400,7410,7430,7450,7470,7505,7530,8350,8461,8540

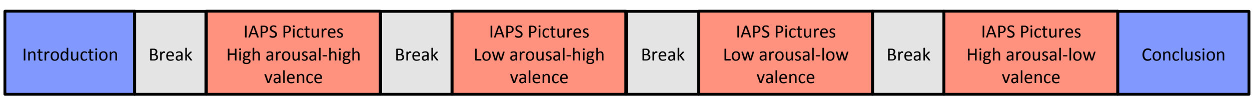


Fig. 4. Flow of the emotional state experiments.

time (t_end) that lead to the largest common time span. As the WMSs collect data continuously and the participant starts and ends the epoch, Case 1 in Fig. 5 refers to the expected circumstance in terms of signal duration. In Case 1, smartphone data collection starts and ends earlier than that of WMSs. However, we encounter situations where the participant forgets to turn on the WMSs (Case 2 and Case 3), WMSs lose their connection, or their battery dies (Case 3 and Case 4). After performing data alignment, t_start and t_end are provided as input to the next stage.

Both data sources (WMSs and smartphone) generate time series data. Each data instance has temporal correlation with the former and subsequent instances. Taking this relationship into account, we divide the collected data into 20 s windows with 5 s shifts in between. We call this stage data windowing. As shown in Fig. 5, data windowing is preceded by data length checking. If the data length ($t\_end - t\_start$) is shorter than the window size (d_window), we discard the data as they have inadequate information. Once the data are filtered through the data length checking stage, they are divided into windows using t_start and t_end information.

WMSs and smartphones exhibit linear and nonlinear properties that need to be captured in the feature extraction stage. In the first step of feature extraction, in line with studies in [74] and [75], we calculate the 4th-order Daubechies Wavelet transform (for both the approximation and detail coefficients) and Fourier transform of the data in each window. Then, from each transform and the original data, we compute the mean, median, standard deviation, maximum, minimum, and the difference between maximum and minimum values. The original signal and its Fourier transform each leads to six features. On the other hand, the Wavelet transform leads to 12 features: six for approximation coefficients and six for detail coefficients. Therefore, the feature extraction block outputs 24 features extracted from a physiological/electromechanical signal. The collected data in the physical and mental state experiments include three-axis accelerometer and three-axis gyroscope electromechanical signals and GSR [measures the electrical activity of the skin (i.e., the skin conductance)], BVP [measures the cardiovascular activity (e.g., heart rate, heart rate variability, etc.)], skin temperature, blood oxygen level, and blood pressure physiological signals. Since the participant submits the measured values of the blood oxygen level and blood pressure once per session, we directly use these values as features. After obtaining the set of linear and nonlinear features, we proceed to the data normalization stage.

The data normalization stage aims at bringing the feature values to the same range, thus avoiding dominance of one feature over the other due to the difference in their range. This stage rescales the feature values using Eq. (1) to the $[-1, 1]$ range. In Eq. (1), the maximum and minimum values are calculated using training data and applied to both

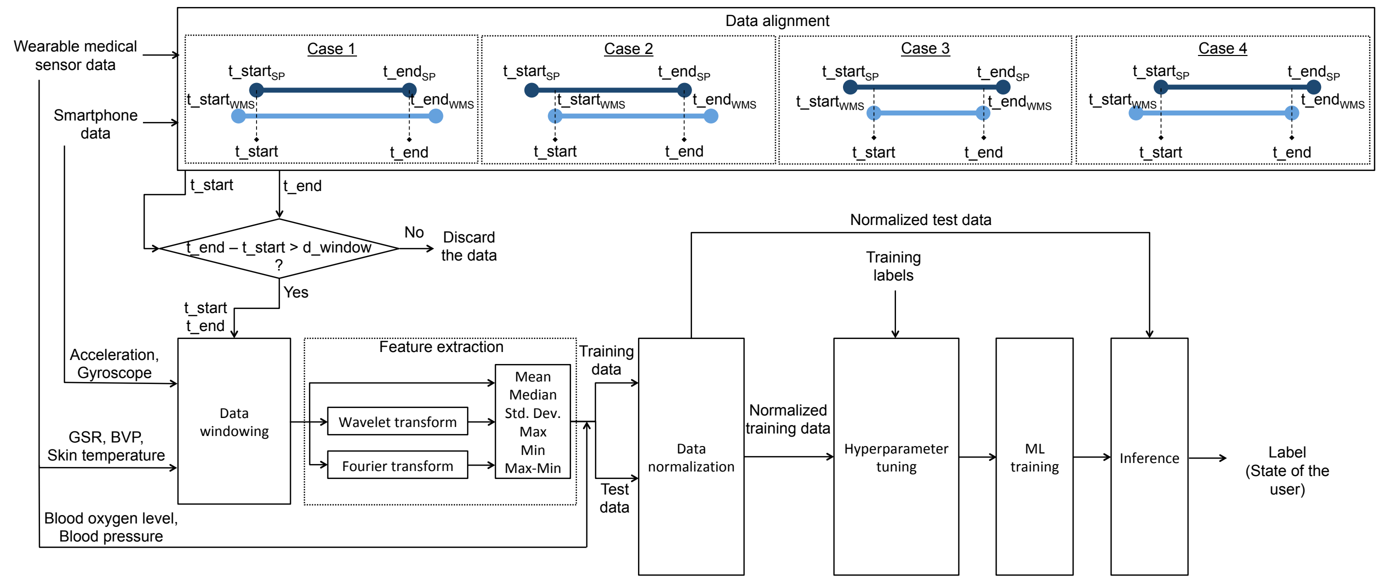


Fig. 5. The YSUY data processing and decision-making stages for physical and mental state experiment. Subscripts SP and WMS stand for smartphone and wearable medical sensors, respectively.

training and testing data.

$$d_i' = 2 \times \frac{d_i - min(d)}{max(d) - min(d)} - 1 \quad (1)$$

The hyperparameter tuning stage takes normalized training data and corresponding labels as input and outputs the best set of hyperparameter values that maximize the classification performance. We implement this stage using the framework introduced in [76]. It uses Bayesian optimization with Gaussian process (GP). It starts with a prior belief over the possible hyperparameter values and their classification performance. In each iteration, it updates GP using the classification performance and chosen hyperparameter values. With the help of an upper confidence bound as the acquisition function, the next set of hyperparameter values is determined. Then, the same loop is executed to determine the classification performance and GP update. This process continues until the maximum number of iterations is reached.

After obtaining the best set of hyperparameter values, YSUY trains the ML algorithm with the normalized training data and labels. This stage yields ML models for the physical and mental states of the users. YSUY then proceeds to the inference stage, where it obtains the state information corresponding to an unlabeled data instance.

4.3.2 Emotional State

Emotional state experiments do not depend on participant reports to avoid unintentional biases introduced due to environmental factors and participant characteristics. Thus, the participants do not use the smartphone to log their emotional state information. Instead, the participants are shown a set of IAPS pictures, whose arousal-valence ratings and, hence, the induced emotions are known. Moreover, we use the respiration belt as an additional WMS to obtain respiratory information. The YSUY data processing and decision-making stages for emotional state experiments is shown in Fig. 6.

Data processing of the emotional state experiments starts with windowing of the WMS data. In line with the physical and mental state experiments, collected data are divided into 20 s windows with 5 s shifts in between. Then, we extract the 24 linear and nonlinear features described in Section 4.3.1 from the respiration, GSR, BVP, and skin temperature signals. We also detect the peaks and valleys in the respiration data that represent inhalation and exhalation, respectively. We extract 14 features from this peak-valley information. The total number of peaks-valleys, and mean, median, and standard deviation of the index and magnitude of the peaks-valleys account for the 14 features. We extract three features (mean, median, and standard deviation) from blood oxygen level and systolic-diastolic blood pressure for each measurement, resulting in nine features per window. We then perform data normalization, hyperparameter tuning, ML training, and inference, as described in Section 4.3.1, to assess the emotional state of the user.

5 Experimental Results and Discussion

Next, we present and discuss experimental results for the physical, mental, and emotional state detection modules of YSUY.

5.1 Physical and Mental State Detection

Recall that we collect physical and mental state data while the participants undergo their normal daily routine. Although we tracked data collection and kept in touch with the participants to ensure data consistency and provided help whenever needed, we did not specify the physical/mental states that need to be logged through the YSUY app or the overall data collection duration. The goal was to capture participant responses and assess the YSUY state detection capability in real-life situations.

Table 3 shows the physical and mental states declared by various participants and the total experiment duration.

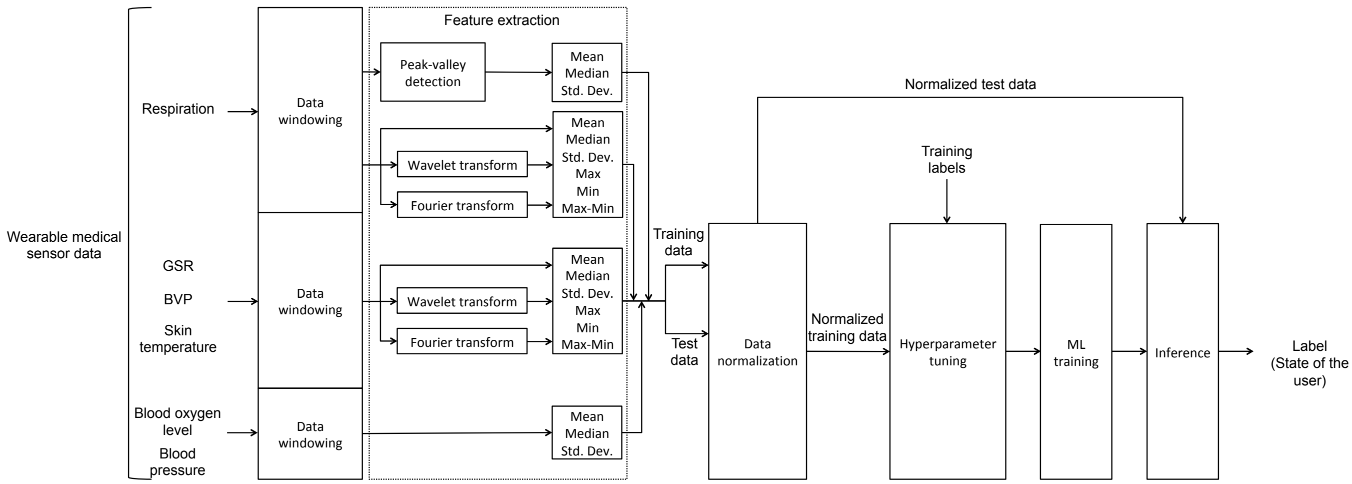


Fig. 6. The YSUY data processing and decision-making stages for the emotional state experiment.

The participants declare three to four different physical states and three to five different mental states during data collection (for a minimum of two days and a maximum of four days). Next, we process the data and extract features from the signals collected through the WMSs and smartphone. Since some of the participants did not provide or only partially provided their blood oxygen level and blood pressure measurements, we did not include these signals in the data processing stage. The remaining signals, and hence the extracted features, form a time series. Therefore, we use the first 80% of the data instances as training data and the remaining as test data. Since the set of declared states and its cardinality are not uniform across the participants, we build user-specific physical and mental state classifiers based on MLP (with one hidden layer), SVM with RBF kernel, and kNN algorithms. We optimize the hyperparameters of these algorithms using the training data of the corresponding participant and a Bayesian optimization framework [76].

Table 4 shows the accuracy and F1 scores for each participant. Accuracy (ACC) is calculated by dividing the total number of true positives (TP) and true negatives (TN) with the total number of instances in the test set [i.e., TP, TN, false positives (FP), and false negatives (FN)]. The F1 score (F1) is calculated as the unweighted mean of the F1 score of each class. The F1 score is itself the harmonic mean of precision (PREC) and recall (REC). Eq. (2) and Eq. (3), respectively, show the equations for deriving ACC and F1.

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

$$F_1 = \frac{\sum_{i=1}^{n_{class}} 2 * PREC_i * REC_i / (PREC_i + REC_i)}{n_{class}},$$
$$\text{where } PREC = \frac{TP}{TP + FP}, REC = \frac{TP}{TP + FN}, \text{and}$$
$$n_{class} \text{ is the total number of classes within the dataset} \tag{3}$$

As we can see, for the physical state, the MLP and kNN/SVM algorithms have the highest average classification accuracy and F1 score, respectively. All three algorithms achieve a perfect accuracy and F1 score of 1.0 for Participant 5. For the remaining participants, MLP and SVM exhibit comparable accuracy and F1 score values. kNN has a similar trend except for Participant 3. For Participant 1, while SVM achieves a classification performance above 0.91, MLP and kNN obtain the lowest accuracy and F1 score values relative to other participants. This may be due to the fact that the amount of data is not sufficient for MLP and SVM algorithms for this participant to distinguish among the four states (driving, stationary, typing, and walking) accurately. Although Participant 1 has the same four declared physical states and the same data collection duration as Participant 7, the physiological responses of each participant are different. This supports our personalized state detection approach.

Overall, YSUY determines the physical state of its users with high classification performance (approximately 0.9) even though the physical state data are collected while the participants go about their daily routines with no restrictions imposed on physical actions and data collection duration. This bodes well for the use of YSUY in real-world situations.

For the mental state as well, YSUY achieves a classification performance around 0.90 for all three algorithms, with kNN having a small edge over the other two. kNN has the lowest classification performance (0.822 accuracy and 0.806 F1 score) for Participant 3. When we analyzed the confusion matrix for this participant, we found that the classifier is not able to distinguish between the 'Normal' and 'Full' states. There may be two possible reasons for this: either the collected data amount is not sufficient or the participant was not able to assess the mental state clearly while logging it through the YSUY app.

Next, we analyze the relationship between the physical and mental states. Fig. 7 shows the links between the physical and mental state reports from the participants. Line thickness indicates the frequency of occurrence of the connections (thicker the line, more frequent the occurrence). The participants reported walking (a physical state) and normal (a mental state) in 13% of the YSUY app logs. They reported stationary-normal, typing-preoccupied, and walking-full state combinations in 7%, driving-normal and stationary-sleepy in 6%, and stationary-

TABLE 3
Declared Physical and Mental States for Each Participant

Participant #	Declared Physical States	Declared Mental States	Time Span (days)
1	Driving, Stationary, Typing, Walking	Full, Normal, Preoccupied, Sleepy-Full	3
2	Driving, Sleeping, Stationary, Walking	Full, Normal, Sleepy, Thirsty	4
3	Driving, Stationary, Walking	Full, Hungry, Normal, Sleepy, Tired	2
4	Sleeping, Stationary, Walking	Anxious, Normal, Sleepy	2
5	Stationary, Typing, Walking	Excited-Preoccupied, Full, Preoccupied, Sleepy-Thirsty, Sleepy-Tired-Full	3
6	Stationary, Typing, Walking	Full, Hungry, Normal, Sleepy, Preoccupied, Tired	3
7	Driving, Stationary, Typing, Walking	Bored, Normal, Preoccupied, Tired	3

TABLE 4
Classification Performance of the Physical State and Mental State Classifiers

Participant #	Physical State						Mental State					
	MLP		SVM		kNN		MLP		SVM		kNN	
	ACC	F1	ACC	F1	ACC	F1	ACC	F1	ACC	F1	ACC	F1
1	0.746	0.767	0.679	0.711	0.911	0.911	0.969	0.961	0.978	0.966	0.960	0.954
2	0.951	0.896	0.960	0.937	0.897	0.850	0.714	0.794	0.772	0.815	0.848	0.870
3	0.890	0.842	0.898	0.839	0.677	0.647	0.830	0.817	0.817	0.827	0.822	0.806
4	0.984	0.988	0.974	0.980	0.974	0.980	0.995	0.996	0.966	0.941	0.986	0.989
5	1.000	1.000	1.000	1.000	1.000	1.000	0.954	0.952	0.967	0.966	0.992	0.992
6	0.890	0.704	0.927	0.833	0.932	0.874	0.871	0.881	0.881	0.901	0.855	0.882
7	0.925	0.882	0.824	0.823	0.903	0.862	0.946	0.932	0.946	0.947	0.917	0.925
Average	0.912	0.868	0.894	0.875	0.899	0.875	0.897	0.905	0.904	0.909	0.911	0.917

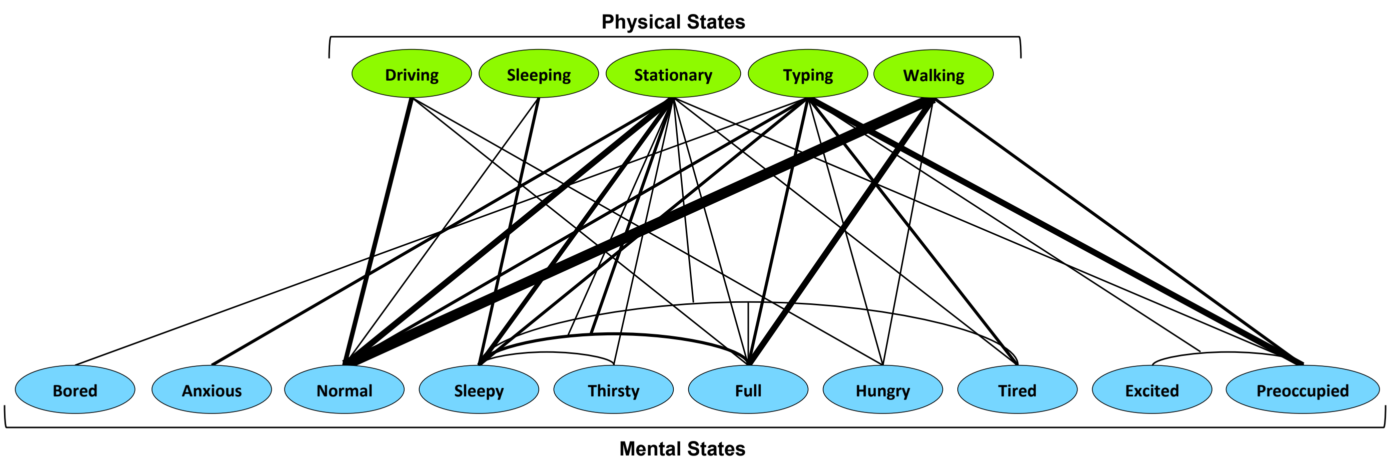


Fig. 7. Links between the physical and mental states. Thicker line corresponds to more frequent physical-mental state reporting.

sleepy-full, typing-full, sleeping-sleepy, stationary-anxious, typing-sleepy, typing-normal, typing-tired, and walking-preoccupied in 4% of the logs. Each of the remaining reports accounted for 2% of the logs. Recall that the features used in these classifications are extracted from both physiological and electromechanical signals. Since participants experience physical and mental states simultaneously and both states have an effect on physiological and electromechanical signals, there is a relationship between the physical and mental states. In Fig. 7, we indicate how frequently the links occur. However, the absence of a link may also carry a lot of information. For example, the walking physical state is never linked with the anxious mental state. However, the stationary physical state is linked with the anxious mental state in 4% of the logs. This might indicate that walking may be helpful in avoiding a negative mental state like anxiety. Similarly, the sleeping physical state is not linked with the bored or anxious mental states, but linked with the normal mental state. The reason for this is self-evident.

5.2 Emotional State Detection

The physical and mental state experiments do not have to follow a specific experimental protocol. Using the provided WMSs and smartphone, the participants continue with their daily lives, provide labels through the YSUY app at a time of their choosing, and return the borrowed items after a minimum of two days. However, the emotional state experiments follow an experimental protocol (Fig. 4) based on IAPS pictures, but incorporate randomness encountered in real-life through random picture selection from each quadrant in the two-dimensional emotion chart (Fig. 3). IAPS pictures have associated with them validated arousal-valence ratings. Therefore, the effect of each picture on the participant and the corresponding emotion are known.

This eliminates the need for the participants to report their emotional state, which may include unintentional biases.

Table 5 shows the classification performance of YSUY's emotion detection module. As discussed in Section 4.2, YSUY focuses on the four quadrants of the emotion chart: high arousal-high valence, low arousal-high valence, low arousal-low valence, and high arousal-low valence. The table shows that YSUY can distinguish among these four quadrants quite accurately, with a perfect 1.00 accuracy and F1 score in many cases.

For applications that require classification of emotions into just two classes: positive (high valence) and negative (low valence), we present results in Table 6. YSUY has perfect classification performance from at least two algorithms, except for Participant 1.

TABLE 5
Classification Performance of the Emotional State Classifier (Four classes: high arousal-high valence, low arousal-high valence, low arousal-low valence, and high arousal-low valence)

Participant #	MLP		SVM		kNN	
	ACC	F1	ACC	F1	ACC	F1
8	0.913	0.910	0.900	0.896	0.888	0.882
9	1.000	1.000	1.000	1.000	1.000	1.000
10	0.950	0.949	0.938	0.937	1.000	1.000
11	1.000	1.000	0.888	0.891	0.950	0.949
12	1.000	1.000	1.000	1.000	1.000	1.000
13	1.000	1.000	1.000	1.000	1.000	1.000
14	0.988	0.987	1.000	1.000	0.988	0.987
15	1.000	1.000	0.950	0.949	1.000	1.000
16	0.838	0.832	0.813	0.803	0.813	0.805
17	0.969	0.968	1.000	1.000	1.000	1.000
Average	0.969	0.968	0.949	0.948	0.964	0.962

TABLE 6
Classification Performance of the Emotional State Classifier (Two classes: high valence, low valence)

Participant #	MLP		SVM		kNN	
	ACC	F1	ACC	F1	ACC	F1
8	0.913	0.912	0.775	0.763	0.900	0.899
9	1.000	1.000	1.000	1.000	1.000	1.000
10	1.000	1.000	1.000	1.000	1.000	1.000
11	1.000	1.000	1.000	1.000	0.925	0.925
12	1.000	1.000	1.000	1.000	1.000	1.000
13	1.000	1.000	1.000	1.000	1.000	1.000
14	1.000	1.000	1.000	1.000	1.000	1.000
15	1.000	1.000	1.000	1.000	1.000	1.000
16	1.000	1.000	1.000	1.000	1.000	1.000
17	1.000	1.000	1.000	1.000	1.000	1.000
Average	0.991	0.991	0.978	0.976	0.983	0.982

6 APPLICATION OF YSUY TO HUMAN NEEDS

In this section, we discuss how YSUY can address basic human needs in four different dimensions: 'being,' 'doing,' 'having,' and 'interacting.'

6.1 Being

The 'being' aspect of subsistence requires the physical and mental health needs to be satisfied. YSUY addresses the physical health need by continuously tracking the physical activity of the users through physiological and electromechanical signals obtained from the WMSs and smartphone, respectively. Physical activities are known to have a positive effect on overall well-being of the users [77]. YSUY can also help shed light on the mental health of the users and help discover various anomalies, e.g., eating disorders, negative feelings, reduced physical activity, mood swing, etc. [78], through the monitoring of the physical, mental, and emotional states of the users. Continuous classification of these states also reveals deviations from regular habits of the users and provides an opportunity for early diagnosis.

YSUY satisfies the protection need by broadly targeting users and various circumstances they find themselves in. As opposed to previously introduced care systems that focus on specific age groups, e.g., infant/elderly care [79], [80], [81], gender, or health condition, e.g., cancer [82], diabetes [83], hypertension [84], etc., YSUY's physical/mental/emotional state analysis is applicable to everyone. Thus, YSUY could be used as a basis for a broader set of care systems in the future.

YSUY targets affection, participation, leisure, and identity through the emotional state classifier since respect, sense of humour, generosity, sensuality, receptiveness, dedication, sense of belonging, etc., require a positive attitude on part of the individual. Experimental results presented in Section 5.2 show that YSUY is able to distinguish among the four quadrants of the emotion chart with MLP, SVM, and kNN algorithms exhibiting an average accuracy of 0.969, 0.949, and 0.964, respectively. These emotional state classifications can be used to activate biofeedback mechanisms to direct the users towards positive emotions.

YSUY directly targets the understanding need through continuous reporting of the physical/mental/emotional states of the users along with the time information. Continuous reporting and availability of past results can be used to automatically trigger critical thinking, resembling the logic-based therapy (LBT) employed in psychiatry. In LBT, critical thinking techniques are practised to identify and show patients the irrational or contradictory aspects of their behavior [85].

The physical/mental/emotional state classifications provided by YSUY create self-awareness in the users about their abilities, skills, and responses. This targets the creation need.

The 'being' dimension of freedom includes autonomy, passion, self-esteem, and open-mindedness. Self-esteem is tackled through self-awareness [86], as described earlier. YSUY enhances open-mindedness by enabling the users to look at data points from different angles. In other words, YSUY provides multiple perspectives on a single data epoch. However, in order to enhance open-mindedness further, in the future, YSUY could be augmented beyond state classification to suggestions for a variety of user responses through an app. Since open-mindedness requires embracing, accepting, or cultivating different points of views [87], the updated YSUY may be able to bring users out of their comfort zone and enable them to benefit from a variety of solutions.

6.2 Having

The 'having' dimension of subsistence targets food, shelter, and work. YSUY identifies hunger through mental state analyses. It determines whether the users are full or hungry with a classification accuracy and F1 score of 0.911

and 0.917, respectively. Moreover, the time information associated with the classification reveals the duration of hunger and its frequency, which can be used to assess the significance of the problem. YSUY can provide hints for shelter- and work-related issues with the help of physical activity, emotion tracking, and mental state analysis components. For example, an unemployed person may exhibit less physical activity or higher mental stress, which may increase blood pressure [88], depression, anxiety [89], and tendency towards an unhealthy diet [90]. Similarly, shelter problems may lead to increased alcohol usage, negative feelings, and sleep problems [91], [92]. YSUY targets the type, duration, and frequency of negative feelings, blood pressure level, alcohol usage, and eating habits through detailed physical, emotional, and mental state analyses. YSUY classification results need not just be for personal consumption. With user permission, if the collective YSUY results from a large number of individuals are shared with accredited organizations without revealing user identities, YSUY could become influential on a large scale. Collective YSUY results could be used to assess the states/regions of a country that require action to satisfy the 'having' dimension of subsistence, e.g., food, shelter, work, etc. This could lead to a better allocation of limited resources. The collective YSUY results may also be helpful for the protection and understanding needs since social security, health systems, work, literature, policies, and educational tools are best tackled at governmental and legislative levels. Population-level well-being results could guide related organizations on where the most resources are needed, e.g., for social security, health systems, employment, protection plans, retirement policies, educational tools, etc. Currently, the main means of assessing the well-being of the population is through surveys and questionnaires [93], [94]. While YSUY does not eliminate the need to collect data in this fashion, it provides a continuous source of rich data that can complement surveys/questionnaires, so that a more accurate view of the state of the population can be arrived at.

In the 'having' dimension of affection, friendships and relationship with nature are listed. YSUY addresses this need directly by trying to understand the users and providing feedback on their physical, mental, and emotional states, as if it were their friend. However, unlike a real-world friend, YSUY is available around the clock. It may also be helpful to the users in terms of navigating the environment in the sense that the YSUY classification results may help users reason about the link between various environmental factors and their states.

YSUY targets some elements of the participation need (responsibilities and duties) through the biofeedback mechanism [95], [96].

The leisure need requires low-intensity positive emotions. These emotions reside in the low arousal-high valence quadrant. YSUY targets this need through the emotional state classifier and gives feedback to users about the quality of their leisure. Users could also be exposed to positive emotion-inducing inputs, such as good news and pictures, positive quotes, classical music, and micro-meditation [30].

YSUY targets some aspects of the creation need through the mechanism discussed in Section 6.1. The self-awareness created by YSUY can encourage users to participate in related activities and monitor how they respond to this participation.

Features of the identity need are language, religion, work, customs, and values. Currently, YSUY does not address these features. However, in future work, we would like to integrate user preferences into decision-making by retraining the models at predefined intervals. Moreover, we would like to provide YSUY outputs in different languages in order to enhance its cultural coverage.

In the 'having' dimension of freedom, equal rights is listed. YSUY does not do much in this regard.

6.3 Doing

YSUY targets the 'doing' dimension of subsistence and creation with the approach discussed in Section 6.2.

For protection, understanding, and identity, the physical/mental/emotional state classification YSUY provides to the users can be used to activate a biofeedback mechanism, whose effectiveness has been verified in various studies [95], [96]. Since YSUY possesses historical data on the users, the trend lines of how useful an action is can be drawn. Feedback from YSUY also provides an opportunity to satisfy the participation need of users by verifying their state and encouraging them to share opinions in real-life situations. Feedback can also be provided in the reverse direction: from the users to YSUY through the smartphone app. This feedback can be on whether the users agree with the state classification YSUY provides. This can be taken advantage of when YSUY is retrained. Thus, cooperation and expression of opinion from the users can lead to better personalization of YSUY to user needs. Moreover, for the affection need, the biofeedback mechanism triggered through emotional analysis can enable greater sharing, caring, and emotional expression.

The leisure need requires the following features to be satisfied: day-dreaming, remembering, relaxing, and having fun. These features require positive emotions with low intensities, which reside in the low arousal-high valence quadrant. YSUY can thus give feedback to the users about the quality of their leisure.

Freedom requires dissenting, choosing, running risks, and developing awareness. These can be addressed in future work by developing modules that provide separate solutions for each of the states: physical, mental, and emotional.

6.4 Interacting

The 'interacting' dimension refers to the environments (e.g., living environments, social settings, schools, families, universities, communities, private and intimate spaces of togetherness, associations, parties, churches, neighborhoods, and workshops) corresponding to each of the fundamental human needs. YSUY targets the 'interacting' dimension of these needs through both the smartphone and WMSs. The smartphone provides location information through a global positioning system (GPS) sensor or assisted GPS or differential GPS [97] and smartphone/WMSs indicate the physical, mental, and emotional states of the users. Thus, the state information can be correlated with user location or environment, offering the possibility for ML applications to provide a location- and state-specific response. Moreover, the combination of state and location information can enable the suitability of the corresponding social environment to be assessed.

7 Discussion

YSUY analyzes three states of its users to understand them and target their fundamental human needs. The overall system is shown to have 91.2%, 91.1%, and 96.9%/99.1% physical, mental, and 4-class/2-class emotional state detection accuracy, respectively. The links between the physical and mental states have been presented. Moreover, the role YSUY can play in terms of satisfying Max-Neef's 36-cell matrix has been discussed in detail. The discussion points to the insufficiency of individual reports of physical, mental, or emotional states in the context of satisfying the fundamental human needs. This requires the combined information of all three states.

In Table 7, we compare YSUY with previous physical, mental, and emotional-state related studies. The table summarizes the physical, mental, and emotional states, links among them, whether the experiments are performed in a real-life situation (i.e., an uncontrolled environment), whether their effect on satisfiability of fundamental human needs is analyzed, and the overall physical/mental/emotional state detection accuracy. All the studies focus on a single state (e.g., physical, mental, or emotional). They do not consider the other states, therefore ignore the links in between. However, as shown in Section 6, assesing the fulfillment of human needs requires state analyses in different dimensions. The study in [102] does not analyze mental or emotional states, but assesses the location information in addition to the physical state of the users. Thus, it does highlight the need for multi-aspect analyses. The study in [110] also focuses on a single state (emotional); however, it establishes communication with the subject (provides/receives feedback) during the experiments. Moreover, as none of these studies analyze more than one human state, they cannot analyze the in-between links. However, as shown in YSUY, physiological signals predict all three states with over 90% classification performance. Since the states are assessed through the same set of physiological signals, there exist links in between the states. We presented these links for physical and mental states. However, we could not analyze the links for the emotional state as its experiment is carried out separately. Studies in [102], [103], [105], [106], [111] and [112] are based on real-life experiments. The study in [101] is based on experiments partially carried out in a real-life and partially in a controlled environment. The remaining studies limit the participant to a specific experimental protocol/environment, and do not introduce any randomness. Moreover, none of the studies analyze their designs in the context of addressing fundamental human needs. Although these studies report successful physical/mental/emotional state detection performance, they remain task-oriented instead of being user-centric. This is the main reason behind the current gap between AI technologies and humans.

YSUY gets around the above-mentioned problems. It analyses user states from three different perspectives: physical, mental, and emotional. It depends on experiments performed in real-life situations, considers the links between the states, and targets fulfilment of fundamental human needs. It keeps users at the center of its design, aided by high state classification performance.

8 Conclusion and Future Work

We described a user-centered operational flow for AI technologies. Rather than directly focusing on the task, as traditional approaches do, our flow targets understanding the users first and then completing the task. The traditional approach has been shown to be effective for various ML applications. However, understanding the users can augment the efficacy of such approaches. We introduced YSUY, an ML-based system for strengthening human-AI interactions and enhancing the quality and timing of various processes. YSUY places major emphasis on understanding the various states (physical, mental, and emotional) of the users before completing the task. This is aimed at closing the human need/AI gap. We have implemented YSUY with WMSs and a smartphone, then experimented with it in the context of the natural flow of participants' lives. We obtained physical, mental, and four-class (two-class) emotional state classification accuracy values of 91.2%, 91.1%, and 96.9% (99.1%), respectively. We discussed how YSUY can be used to address basic human needs, as enunciated in Max-Neef's 36-cell matrix. Since YSUY has the potential to address most of these cells, it can be further developed to bridge the human need/AI gap.

Possible future research directions are as follows. First, the states of close associates of the users or environmental factors, such as weather, air quality, water quality, etc., can be integrated into the YSUY models. Second, further analyses of a larger more diverse population needs to be performed to broaden YSUY's applicability. For physical and mental state analyses, we collected data from seven individuals, and for the emotional state analysis, from 10 individuals. They were either undergraduate or graduate students at Princeton University. However, the applicability of YSUY is not limited to a particular age group, gender, ethnicity, or health condition. Third, the effect of YSUY's state reports on the user's actions and emotions can be used to update the current YSUY model and implement a suggestion mechanism. Once YSUY determines the user state, the user can take advantage of a biofeedback mechanism, whose effectiveness has been verified earlier [95], [96]. However, in the future, without waiting for the user to take action, YSUY can offer multiple personalized suggestions, depending on the current state of the user. Finally, the number of classes in physical, mental, and emotional states can be increased to cover a larger set of conditions.

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TABLE 7
Physical/Mental/Emotional State Related Studies and Corresponding Information on Setting of the Experiment, and Accuracy

Paper	Physical States Analyzed	Mental States Analyzed	Emotional States Analyzed	Links Between the States Analyzed	Experiments based on Real-life	Satisfiability of Human Needs Analyzed	ACC (%)
[98]	Sitting down, Standing up, Reaching, Walking, Turning	-	-	-	No	No	90.0
[99]	Sawing, Filing/ Drilling, Sanding, Screwing, etc.	-	-	-	No	No	98.3
[100]	Lying, Walking (Slow/ Normal/Fast), Fall (Active/, Inactive/Chair), Sit-to-stand, etc.	-	-	-	No	No	90.8
[101]	Lying, Sitting/ Standing, Walking, Running, Cycling, Rowing, Playing football	-	-	-	Yes/No	No	89.0
[102]	Walking, Lying, Bicycling, Running, Bathing, Sleeping, etc.	-	-	-	Yes	No	87.0
[103]	Sitting, Laying Standing, Walking, Jogging	-	-	-	Yes	No	99.0
[104]	-	Drowsy, Very drowsy, Awake	-	-	No	No	80.6
[105]	-	Depressive, Normal, Manic	-	-	Yes	No	76.4
[106]	-	Anxious/ Depressed	-	-	Yes	No	57.7
[107]	-	-	No emotion, Hate, Anger, Grief, Platonic love, Romantic love, Reverence, Joy	-	No	No	81.3
[108]	-	-	Sadness, Disgust	-	No	No	59.8
[109]	-	-	Anger, Boredom, Disgust, Fear, Happiness, Sadness, Neutral	-	No	No	81.1
[110]	-	-	Positive valence/ Low arousal/High Dominance, Negative Valence/High Arousal/Low Dominance	-	No	No	92.6
[111]	-	-	Anxiety, Boredom, Engagement	-	Yes	No	63.0
[112]	-	-	Positive/High arousal, Negative/High arousal, Negative/Low arousal, Positive/Low arousal	-	Yes	No	95.0
YSUY	**Driving, Sleeping, Stationary, Typing, Walking**	**Bored, Anxious, Normal, Sleepy, Thirsty, Full, Hungry, Tired, Excited, Preoccupied**	**High arousal-High valence, Low arousal-High valence, Low arousal-Low valence, High arousal-Low valence**	**Physical-Mental**	**Yes**	**Yes**	**91.2 (Physical) 91.1 (Mental) 96.9 (Emotional-4) 99.1 (Emotional-2)**

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He has co-authored or co-edited five books titled Testing and Reliable Design of CMOS Circuits (Kluwer, 1990), High-Level Power Analysis and Optimization (Kluwer, 1998), Testing of Digital Systems (Cambridge University Press, 2003), Switching and Finite Automata Theory, 3rd edition (Cambridge University Press, 2009), and Nanoelectronic Circuit Design (Springer, 2010). He has also authored 15 book chapters. He has authored or co-authored more than 440 technical papers. He has coauthored 14 papers, which have won various awards. These include the Best Paper Award at ICCD'93, FTCS'97, ICVLSID'98, DAC'99, PDCS'02, ICVLSID'03, CODES'06, ICCD'09, and CLOUD'10. A paper of his was selected for "The Best of ICCAD: A collection of the best IEEE International Conference on Computer-Aided Design papers of the past 20 years," two papers by IEEE Micro Magazine as one of the top picks from the 2005 and 2007 Computer Architecture conferences, and two others as being among the most influential papers of the last 10 years at IEEE Design Automation and Test in Europe Conference. He has co-authored another six papers that have been nominated for best paper awards. He has received 17 U.S. patents.