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HUMAN STRESS PREDICTION

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ABSTRACT

Stress is a part of daily life that most people have to deal with from time to time. But chronic stress or high levels of stress can affect our safety and disrupt our normal life . Early diagnosis of mental illnesses can prevent many health problems. When a per son is stressed, heat, electricity, impedance, sound, light, etc. Many biological syste ms can be changed and stress can be detected using these biological signals. This a rticle presents a different learning and deep learning method for detecting anxiety in humans by using many data collected from physical objects and movements, which can prevent various health problems in humans. Data from standard sensors such a s triaxial acceleration (ACC), electrocardiogram (ECG), blood volume pulse (BVP), b ody temperature (TEMP), respiration (RESP), electromyography (EMG), and electro dermal activity activity (EDA) are interconnected throughout our product. is related. b ody. events – sports, neutral and stressful, retrieved from the WESAD dataset. Evalu ate and compare the accuracy of three-category (fun, basic, stress) and binary (stressed and unstressed) classification, Ada Boost, and kernels using machine learning such as k-nearest neighbor, linear discriminant analysis, random forests, and decision trees Su pport Vector Machine . Additionally, simple feedforward deep learning neural networ ks have also been introduced for three- and two-class classification. Using machine learning during the research, the accuracy rate of 81.65% and 93.20% in three-group and two-group problems based on deep learning was as high as 84.32% and 95.21%, respec tively. Plethysmography, stressors, accelerometers, dichotomy, sudomotor activity, c onvex optimization

I. According to S. Palmer [17], “Anxiety is often defined as a mental and behavioral di sorder resulting from the imbalance between the needs of people and the nature of the capital that meets the needs created." Stress can cause negative effects on the mind and body, such as irregular heartbeat, aka irregular heartbeat. Arrhythmias and depression. According to the American Institute of Stress [14] 80% of employees experience stress at work, nearly half say they need help learning how to manage stress, and 42% say their employees need that help. According to the Health and Safety Executive (HSE), work-related stress, depression or anxiety accounts for 44% of all health incidents at work and 54% of all working days lost. percentage of health in 2018/19 due to illness[15]. Research in humans and animals suggests that stress can affect the immune system and increase the risk of cancer. These statistics and the effects of stress on human health require systems that can diagnose stress to reduce stress through self-intervention or medication when necessary. Surveys for the assessment of stress in humans. There is a lot of uncertainty and ambiguity in this method because it depends on individual answers and people will be afraid to answer the questions. Worry about losing your job, approaching the end of your job, etc. When it comes to psychological problems, the situation can be stressful. This stressful situation causes many stress hormones, which in turn cause associated physical changes such as faster heart rate, faster breathing, muscle tension, and the appearance of sweat beads. During these physiological changes, biological problems occur in affected individuals. These biosignals help detect stress by measuring a person's body temperature. Various physical sensors are used for automatic pressure measurement. This test can help monitor stress to prevent dangerous stress-related diseases. pressure). To achieve this goal, many steps are taken, such as understanding the structure and format of publicly available WESAD data, cleaning and transforming the data into aggregated products suitable for the development of machine learning and deep learning, search and create various classifications. model and compare. 2. Related work

In recent years, efforts have been made to measure stress and obtain predictions from machine learning models trained using the body's response to stress and emotions.

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INTRODUCTION

the WESAD dataset on wear pressure and stress and made it publicly available. To collect this data, they selected 15 people and placed wearable devices such as Resp iBAN Professional and Empatica E4 on physical Activity and other physiological data , recording triaxial acceleration, electrocardiogram, blood volume pulse, body temper ature, respiration, electromyography, and electrodermal performance. . Basic, entert ainment, stress, emotional etc. They share content regarding various stress factors s uch as. They used five machine learning algorithms for stress condition detection an d compared their performance: K-nearest neighbor (KNN), linear discriminant analysis (LDA), random forest (RF), deci sion tree (DT), AdaBoost (AB). When considered as a three-category (fun vs. stressful) and binary (depressed vs. stress-free) proportion problem using similar features and classical systems, the success ra te of the learning process is approximately 80.34% and 93.12%. .

Jacqueline Wijsman et al. [7] also used a device that measures body temperature to detect stress. They recorded the participants' electrocardiogram, skin conductance, r espiration and electromyogram, from which they calculated a total of 19 physical cha racteristics. For further analysis, after examining the correlation and normalization ei genvalues, one of the 9 features was selected from the 19 features and this was red uced to 7 characteristics using the main points panic. Using these features and differ ent products (such as linear Bayes normal classifier, quadratic Bayes normal classifi er, K nearest neighbor classifier, Fisher least squares linear classifier), 80% accurac y under stress is acceptable. The experiment is almost identical to the experiment co nducted by [1], except for the number of participants and minus features. They used three different stressors in their study and compared their results to other stressors u sing only one stressor. Multimodal data were developed by Saskia Koldijk et al. [6] fo r stress studies and model application. The dataset was collected by 25 employees with general knowledge (typing, reading, searching, etc.) under two stressors: time p ressure and email interruptions. The recorded data includes information such as phy sical body, face, computer recording, skin conductance and heart rate.

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SYSTEM REVIEW

The data includes raw and pre-processed and extracted data and is publicly available. Evidence measuring work behavior and attitudes through questions about work, motivation, and other factors. A new approach to stress-related information in the literature. Participants wore the BN-PPGED on their passive hand as a wrist, which has two electrodes on both fingers that measure pulse plethysmography (PPG) and electrodermal activity (EDA) signals. Additionally, PPG autocorrelation signal and heart rate variability (HRV) were extracted using ArqKnowledge software. Support vector machine (SVM) was used to classify people as stressed or non-stressed with 82% accuracy. [3] developed an automatic classification system to analyze the relationship between work and psychological stress based on sensor data: physical body, face, computer system, and physical (electrocardiogram and skin conductance). They found that when similar users were grouped and the model trained on a specific group, the specific model performed as well or better than the general model in almost every case. To distinguish between stressful and non-stressful work, the body provides the most important information in the most useful way. Performance can be further improved by adding face information. They achieved 90% accuracy using the SVM classifier. In addition, G. Giannakakisa et al. [8]. The features examined were mouth movements, eye-related events, camera-based photoplethysmographic estimates of heart rate, and head movement. Participants were asked to sit 50 cm apart in front of a computer monitor with an integrated camera. Methods such as Generalized Likelihood Ratio, Naive Bayes Classifier, Support Vector Machine, K Nearest Neighbor and AdaBoost Classifier have been used and tested. The best classification performance in the exposure phase was achieved using the Adaboost classifier with 91.68% accuracy. [5] used ECG features for stress state classification. ECG was chosen as the main candidate due to its ease of recording due to ECG feature extraction technology and various portable clinical grade recorders. There is no need for a separate respiratory monitor, because respiratory information is detected by the ECG using EDR technology (e.g. ECG-by-respiration), ensuring better ECG results. When RR interval, QT interval and EDR features are used in SVM classification, the accuracy rate is almost 98.6%. However, this result is unsatisfactory because it uses only a single signal, the electrocardiogram, and does not include other vital signs of the body that are important for anxiety.

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TABLE I:-

SUMMARY TABLE OF REVIEWED ARTICLES WITH METHODOLOGY & PERFORMANCE EVALUATION.

Sr. No.	Title	Author	Methodology & Performance
1	Towards Mental Stress Detection Using Wearable Physiological Sen-sors.	Jacqueline Wijsman, Bernard Grundlehner, Hao Liu, Hermie Hermens	ECG, respiration, skin conductance, & EMG of the trapezius muscles was recorded. Accuracy of 80% by kNN(two class) achieved.
2	The SWELL Knowledge Work Dataset for Stress & User Mod-elling Research	Saskia Koldijk , Mark A. Neerincx, and Wessel Kraaij.	Introduce SWELL-KW data-set. Collected data by computer logging, face expression from camera recordings, body postures from a Kinect 3D sensor and heart rate (variability) & skin conductance from body sensors.
3	Stress Detection Using Wearable Physiological Sensors	Virginia Sandulescu, Sally An-drews, David Ellis, et.al.	Used a wrist worn device named BN-PPGED for data collection. Accuracy of 82% was achieved by using SVM.
4	Introducing WESAD, a Multi-modal Dataset for Wearable Stress and Affect Detection	Philip Schmidt, Attila Reiss, Robert Durichen, et.al.	Introduced the WESAD dataset. A benchmark is created on the dataset, using well-known features & standard machine learning methods. Accuracy of 80% (three class) and 93%(two class) was achieved.
5	Detecting Work Stress in Offices by Combining Unobtrusive Sensors	Saskia Koldijk , Mark A. Neerincx, and Wessel Kraaij.	Computer logging, facial expressions, posture of Employees. Accu-racy of 90% using SVM.
6	Design of a Biosignal Based Stress Detection System using Machine Learning Techniques	Md Fahim Rizwan, Rayed Farhad, et.al.	ECG was selected as the primary candidate to stress detection based on RR interval, QT interval, etc. Accuracy of 98% using cubic SVM.
7	Stress and anxiety detection using facial cues from videos	G. Giannakakisa, M.Pediaditisa.	Used video-recorded facial cues and achieved accuracy of 91.68% for classification.
8	Automatic Stress Detection in working environments from smart-phones' accelerometer data: A First Step	Enrique Garcia-Ceja, Venet Os-mani and Oscar Mayora	Used data from the built-in smartphone accelerometer sensor to identify activity that corresponds with stress levels and achieved accuracy of 71%.
9	Continuous stress detection using a wrist device: In laboratory and real life.	M. Gjoreski, H. Gjoreski, and M. Gams.	Achieved 83% accuracy on a binary class problem using data provided from a commercial wrist device.
10	Emotion recognition based on physiological changes in music lis-tening	Elisabeth Andre, Jonghwa Kim	Made users listen to 4 songs to record their emotional arousal and achieved a classification accuracy of 70%.
11	A Machine learning approach for stress detection using a wireless physical activity	B. Padmaja, V. V. Rama Prasad and K. V. N. Sunitha	Used data collected from FITBIT and achieved an accuracy of 62.14%.

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METHODOLOGY

Another area of research was conducted by Enrique Garcia-Ceja et al. [2] It uses data from the smartphone's built-in accelerometer sensor to identify activities that affect stress points. This sensor was chosen because it poses fewer privacy concerns than location, audio, or video recording. Another reason to choose this power meter is its low power consumption, which makes it suitable for insertion into small devices such as fitness trackers. Smartphones were provided to 30 subjects from two different organizations. Using similar user - and user-specific models, they achieved 60% and 71% accuracy, respectively, based on data obtained from a smartphone accelerometer; however, these data turned out to be insufficient for stress research. Classical machine learning algorithms such as random forest are used to classify stress using data to achieve 83% accuracy of the binary class (“no stress” and “stress”) problem [9] provided by the product on the wrist. Elisabeth Andre, Jonghwa Kim [10] asked users to listen to 4 songs to record their emotions and achieved a classification of 70% using context-free EDMC (Emotion-Specific Multilayer Binary Classification). Kurt Plarre et al. In the study [11], participants rated happiness on a four-point scale (0=no, 1=no, 2=yes,

3=yes). When combined with physical measurements obtained with non-visual equipment, binary classification was achieved with 90% accuracy. [12] developed a cognitive system that can distinguish eight states and their five intensities with an independence accuracy of 62.14%. In one study [13], machine learning was applied to data collected by a wireless activity tracker (e.g., FITBIT). Work time, sleep time, sleep, body mass index, aerobic exercise, maximum heart rate, fat burning, etc. for stress control. Various features are used. Data of Indians working in information technologies and other sectors are included in the system. Table 1 provides a summary of the review articles. This study uses the WESAD dataset, a multimodal physiological/biological signals dataset collected from humans using non-invasive techniques. Using machine learning algorithms such as K-

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Nearest Neighbor (KNN), Linear Discriminant Analysis (LDA), Random Forest (RF), Decision Tree (DT), AdaBoost (AB), and SVM, as well as learning models to easily split topics. according to their stressful situation. This makes the doctor or psychologist doing the manual work more reliable. If, after classification, the person is found to be anxious, appropriate counseling or anti-anxiety medication may be given as needed. We. Methodology

A. Dataset and Feature Extraction

WESAD is the data used for this study. This information was shared and made public by Attila Reiss, Philip Schmidt and others. 2018[1]. This multimodal database collects kinematic data and physical characteristics from 15 individuals on the chest-mounted RespiBAN Professional device and the wrist-mounted Empatica E4. Subjects were included in various studies such as planning, basic conditions, sports, stress, emotions, recovery, and their physical support was recorded. Reference [1] describes in detail the sensor configuration, sensor placement and procedures used to generate this data, which data were collected during the study protocol of the courses. ECG, EDA, electromyography and body temperature. All signals are sampled at 700 Hz. The E4 measures TEMP, EDA, ACC and BVP at sampling frequencies of 4 Hz, 4 Hz, 32 Hz and 64 Hz respectively. The files are organized so that each topic has a folder (SX, where X = topic ID). Each topic contains the following information:

➡ SX readme.txt: Contains information about the topic (SX) and documentation and good information if available. Get all the important facts, including the SX process and answers to the personal survey. , RESP, etc. This folder also contains the following files:

— ACC.csv: 3 lines of text referencing our measurement line.

Signal slope Î´T EMP and slope are used as features. The EDA signal is passed through a low-pass filter at 5 Hz, and then features such as standard deviation, mean, minimum and maximum are calculated [1]. ..., xn is the window of the original data; where x1, x2 etc. They are n points or measured values in a 1-

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second window. The function calculates statistical properties such as mean, standar d deviation, minimum and maximum values
for a given observation using the following numbers (1), (2), (3) and (4), respectively.
br>
– EDA.csv: Data in μS. >μ = 1 x
n i
i=1

= x1 + x2 + �· �· + xn
n

(1)

Split all sensor signals using a 1 second sliding window offset. Feature extraction wa s performed using different types of WESAD datasets, and these features are shown in Table I. These properties are part of those described in [1]

-.. 1 Î£n

(xi − Âμ)2 (2)

.
Calculate standard Various statistics of each axis (i Analyze features such as mean, standard deviation, minimum and maximum values
based on raw ECG, BVP, RESP and TEMP signals. Also maximum BVP

TABLE II
LIST OF EXTRACTED FEATURES FROM WESAD DATASET

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Modality	Features	Description
ACC	$\mu_{ACC,i}$, $\sigma_{ACC,i}$ $min_{ACC,i}$, $max_{ACC,i}$ $i \in \{x, y, z, 3D\}$	Mean, standard deviation, minimum and maximum value for each axis separately and summed over all axes
ECG	μ_{ECG}, σ_{ECG} min_{ECG}, max_{ECG}	Mean, standard deviation, minimum and maximum value of the ECG
BVP	μ_{BVP}, σ_{BVP} min_{BVP}, max_{BVP}, f^{peak}_{BVP}	Mean, standard deviation, minimum, maximum and peak frequency of the BVP
EDA	μ_i, σ_i, min_i, max_i $i \in \{EDA, phasic, tonic, smna\}$	Mean, standard deviation, minimum, maximum value of the EDA signal, SCR/SCL and sparse SMNA driver of phasic component
EMG	μ_{EMG}, σ_{EMG} min_{EMG}, max_{EMG}, f^{peak}_{EMG}	Mean, standard deviation, minimum, maximum and peak frequency of the EMG
RESP	μ_{RESP}, σ_{RESP} min_{RESP}, max_{RESP}	Mean, standard deviation, minimum and maximum value of the RESP
TEMP	μ_{TEMP}, σ_{TEMP} min_{TEMP}, max_{TEMP}, δ_{TEMP}	Mean, standard deviation, minimum, maximum and slope of the TEMP

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$min = u$, where u is minimum among $x_1, x_2, ..., x_n$ (3)

$max = v$, where v is maximum among $x_1, x_2, ..., x_n$ (4)

Additionally, as the raw EDA signal consists of a phasic (skin conductance response (SCR)) and a tonic (referred toas skin conductance level (SCL)) components, they were separated. Once the SCL and SCR components were separ

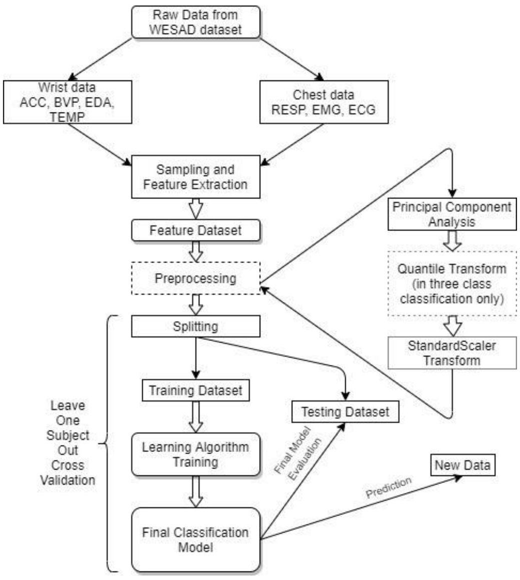

Fig. 1. Schematic flow diagram of Stress Detection Methodology

Same as EDA number. Additionally, the driver's random sudomotor motor nerve acti vity (SMNA) was derived for the phase component and EDA-like features were calculated by optimization using the electrodermal function (cvxED A) [16]. The raw EMG signal was passed through a high-pass filter with a frequency of 5 Hz to remove the DC component. Features of the ind ex such as standard deviation, average, minimum, maximum and maximum value ar e calculated. Pre-processing and classification algorithms

Six machine learning (random forests, decision trees, AdaBoost, k-nearest neighbor, linear discriminant analysis and kernel support vector machines) a nd deep learning neural networks (ANN) were used and their performances - Mance, to compare. As mentioned above, features are first extracted according to the appro

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priate classification algorithm. Two types of classification are used: three-class classification and binary classification. Ternary classification is defined as classifying a person as being in a fun, normal, or stressful situation, while binary classification is defined as classifying a person as anxious or not anxious. Figure 1 shows the schematic flow chart of the pressure measurement method. Features for the resulting data were transformed to follow a normal or normal distribution using the quantile transformer method. Therefore, for a given feature, this transformation usually reveals the most important features and reduces the impact of outliers. A scalar preprocessing method is then used to model the features by subtracting the mean and measuring unit variance. For binary classification problems

Layer (type)	Output Shape	Param #
dense_4 (Dense)	(None, 12)	252
dropout_2 (Dropout)	(None, 12)	0
dense_5 (Dense)	(None, 6)	78
dense_6 (Dense)	(None, 1)	7

Total params: 337
Trainable params: 337
Non-trainable params: 0

Layer (type)	Output Shape	Param #
dense_4 (Dense)	(None, 12)	252
dense_5 (Dense)	(None, 6)	78
dense_6 (Dense)	(None, 3)	21

Total params: 351
Trainable params: 351
Non-trainable params: 0

Fig. 2. Summaries of deep learning architecture for binary (left) and three-class (right) classification.

All machine learning and deep learning algorithms primarily use significance testing with the number 20 and use the full svd solver. Scalar preprocessing is then performed on the generated data after using PCA, as shown in Figure 1. For decision tree and random forest classifiers, the minimum number of samples of the split node in three-level classification is set to 10. and the maximum depth are set to 4 and 9 respectively. In contrast, in the case of binary distribution, the maximum depth is set to a preset value (the node expands until all leaves are cleared or the number of all leaves is less than the number of instances used to split the node). Class AB uses the decision tree as prediction, and the minimum number of samples of its individual line is set to 5 and 10 in three groups and two groups. In the k-Nearest Neighbor algorithm, the number of neighbors in the two classification functio

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ns is set to 9. Additionally, Support Vector Machine classifier is used for classification using the RBF (Radial Basis Function) kernel. Model. In binary classification, 0.25 output is added between the two hidden layers. In the binary classification architecture, the output has a singlet with a sigmoid as the activation function. In contrast, in the three-class model the output has three nodes with softmax activation function. Details of these two models are shown in Figure 2. To use all binary classification algorithms, fun classes (label 0) and base (label 1) are combined to form a new class called stress-free (label 0) and stress is another class (changed to label 1). F1 score (macro average) and accuracy are used to evaluate metrics for learning metrics. It is recommended to use F1-score since many conditions were performed at different lengths during the study protocol, making the study using WESAD an unbalanced classification study. The way people interpret and respond to emotional stimuli affects learning. Therefore personalization

becomes an important issue. Therefore, a leave-one-out (LOSO) cross-validation procedure was used to evaluate each model, and the final accuracy was reported as the average correct across all tests when LOSO passed a test with one exit. education. This allows the model to expand more effectively and efficiently on previously unseen data, making it more autonomous.

RESULTS AND DISCUSSIONS

The proposed study demonstrates two classification tasks based on a person's emotional state to identify stress. First, three classification categories of activities were identified: fun, basic, and stressful. Second, fun and baseline were placed in the non-stress category and a dichotomy was defined: depression versus depression. No stress. Table II shows the performance of the classifier on these two classifications. The lowest possible distribution is successful. Considering all the above features and using a separate learning machine, the accuracy of three-class and binary problem classification reached 81.65% and 93.20%. Moreover, using a simple network connection using deep learning, the accuracy of three classes an

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d binary classification reached 84.32% and 95.21%, respectively. As can be seen from Table II, DT has the best performance among all ML, while kernel SVM has the best performance and ANN has the best overall performance among all distributions. These results are better than the studies of Philip Schmidt et al. [1], the accuracy of three classification tasks is 80.34%, and the accuracy of two classification tasks is 93.12%.

TABLE III

PERFORMANCE OF ALL THE CLASSIFIERS IN THE THREE-CLASS AND BINARY CLASSIFICATION TASKS.

Techniques	three-class		binary	
	F1-score	Accuracy	F1-score	Accuracy
DT	53.73	68.16	84.92	87.59
RF	63.09	75.95	88.32	89.53
AB	67.55	78.19	89.88	91.06
LDA	64.66	74.83	87.60	90.15
kNN	66.76	74.71	84.63	87.92
SVM	73.57	81.65	92.31	93.20
ANN	78.71	84.32	94.24	95.21

CONCLUSION

The research aims to understand the structure and format of the publicly released WESAD data, clean the data and transform it into a collection suitable for the development of machine learning and deep learning, and explore and develop various classification models and

compare them. WESAD data includes information from a variety of body variables, such as triaxial acceleration (ACC), respiration (RESP), electrodermal activity (EDA), electrocardiogram (ECG), body temperature (TEMP), electromyography (EMG), and blood volume pulse. BVP), which is not found in other materials, makes this study suitable for the diagnosis of stress in humans. The model achieves 84.32% and 95.21% accuracy in three-class and two-class problems.

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Due to the large number of participants, caution should be exercised in interpreting these terms. However, our results show that expansion is possible due to the use of L

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OSO analysis. Obtained from the survey. Variables such as facial cues, recorded data, audio/video recordings, FITBIT data used in various studies can be combined with physical data to describe new data. This type of data could be more useful for stress research because it would include almost everything needed for human stress. Duerichen, Kristof Van Laerhoven, “Introduction to WESAD, a multimodal dataset for wearable stress and emotion detection,” 2018 International Conference on Multimodal Interaction. Mayora, – Automatic stress detection on smartphones – Accelerometer data: the first step – arXiv:1510.04221v1 [cs.HC] 14 October 2015. . ” Sensors, Springer International Publishing Switzerland 2015.

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