Stress detection signals on wearable devices

April 24, 2023

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Link to GitHub: http:github.com/ns22771/Stress-detection-signals-on-wearable-devices

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Abstract

This project aims to explore the possibility of incorporating a new feature into a wearable watch equipped with multiple sensors that can alert users when they exhibit signs of stress. To create a trustworthy and accurate stress-monitoring device, it is critical to comprehend the impact of stress on relevant physiological and biochemical factors. This involves investigating how stress affects various bodily functions and identifying measurable indicators that can be used to monitor and detect stress. Here I have analyzed a given set of signals and machine learning pipelines have been employed to predict stress levels based on the available sensor data. The performance evaluation of the model will be presented succinctly, with a focus on explaining how the algorithm arrives at its decisions. The project will ultimately provide a recommendation about what signals can be used to detect stress based on the correlation related to the outcome, feature importance and evaluation of the model's performance, outlining the device's potential to detect and forecast stress levels.

1 Main Findings

1.1 Feature importance in Stress-Predict Dataset

According to the feature importance of random forest classifier the most important features for predicting stress are BVP (Blood Volume Pulse), EDA (Electrodermal Activity), and HR (Heart Rate)), with BVP being the most important for making accurate stress predictions. According to the literature review, physiological variables and classifiers have been used in various studies to monitor physiological stress, but there is no consensus on the optimal measurement approach for stress monitoring. BVP and HR values changed when someone got stressed rather than rest period[1].

1.2 Feature's correlation with outcome label

If analyzing the correlation matrix data of each subject some features have positive corporations and some features have negative correlations. Somehow important features also do not have a significant correlation with the outcome. Finally, it can be found there is a moderate positive correlation is available with some features with the outcome.

1.3 Performance evaluation

Performance is evaluated by the Random Forest classifier model by cross-validation accuracy score,mean accuracy score ,accuracy, precision, recall, MSE and on figure 1

Performance Evaluation

Subject_ID	Subject	Accuracy	F1 Score	MSE	Mean Accuracy	Precision
2	S2	0.779429	0.785724	0.220571	0.484974	0.778879
3	S3	0.775614	0.797916	0.224386	0.446395	0.784859
4	S4	0.766239	0.771312	0.233761	0.521873	0.766281
5	S5	0.806237	0.712103	0.193763	0.655772	0.777374
6	S6	0.768765	0.780704	0.231235	0.558661	0.759875
7	S7	0.798525	0.700065	0.201475	0.553368	0.754898
8	S8	0.792532	0.700906	0.207468	0.512279	0.785313
9	S9	0.789981	0.728775	0.210019	0.488287	0.759839
10	S10	0.788525	0.721226	0.211475	0.494828	0.771748
11	S11	0.792928	0.718533	0.207072	0.519080	0.778277
12	S12	0.802146	0.700326	0.197854	0.607914	0.803869
13	S13	0.791542	0.739106	0.208458	0.487253	0.761518
14	S14	0.805082	0.698829	0.194918	0.593422	0.767349
15	S15	0.806921	0.706416	0.193079	0.524231	0.783125
16	S16	0.799288	0.728521	0.200712	0.537125	0.790630
17	S17	1.000000	0.000000	0.000000	1.000000	0.000000
18	S18	0.805496	0.841675	0.194504	0.561558	0.798674
19	S19	0.776927	0.741913	0.223073	0.568597	0.757630
20	S20	0.794884	0.724299	0.205116	0.592317	0.760436
21	S21	0.787144	0.714471	0.212856	0.522441	0.784537
22	S22	0.786443	0.736252	0.213557	0.515559	0.763772
23	S23	0.775083	0.724769	0.224917	0.482083	0.773433
24	S24	0.791333	0.710803	0.208667	0.539340	0.771459
25	S25	0.803462	0.761035	0.196538	0.697216	0.765448
26	S26	0.790895	0.714417	0.209105	0.519012	0.753840
27	S27	0.805017	0.729824	0.194983	0.601650	0.821315
28	S28	0.819647	0.720796	0.180353	0.607502	0.854492
29	S29	0.800503	0.708079	0.199497	0.566805	0.82188
30	S30	0.794684	0.833181	0.205316	0.516581	0.813736
31	S31	0.794477	0.723458	0.205523	0.627958	0.758616
32	S32	0.789031	0.723359	0.210969	0.608046	0.775594
33	S33	0.808651	0.699245	0.191349	0.655948	0.787809
34	S34	0.799912	0.684911	0.200088	0.628671	0.788697
35	S35	0.795738	0.732225	0.204262	0.553152	0.763056

Figure 1: Performance evaluation of all the subject with all features

Cross validation accuracy score has displayed on figure 2 and there is no accuracy consistence for all the 5 folds.

Performance Evaluation		
Subject_ID	Subject	Accuracy Scores
2	S2	
3	S3	0.3994491 0.31879929 0.49751619 0.51070041 0.50342554
4	S4	0.63945969 0.42125941 0.53976207 0.50466815 0.50906041
5	S5	0.7637525 0.7672085 0.63565725 0.56591586 0.55845549
6	S6	0.52147817 0.6969754 0.5814895 0.50692025 0.48644195
7	S7	0.44443674 0.61031757 0.59554847 0.56096152 0.5555761
8	S8	0.35583325 0.4824228 0.61948771 0.55285583 0.55079377
9	S9	0.29986268 0.48531215 0.58279591 0.5400309 0.53343469
10	S10	0.40070466 0.45429997 0.69995371 0.46916469 0.45001672
11	S11	0.58290044 0.46656817 0.45963399 0.53591002 0.55038723
12	S12	0.59814395 0.64237126 0.66618355 0.57384637 0.55902567
13	S13	0.3465113 0.43071642 0.61182075 0.54195175 0.50526586
14	S14	0.63415487 0.5650236 0.62693644 0.56829156 0.57270522
15	S15	0.23748645 0.62743947 0.63935759 0.55438097 0.56249012
16	S16	0.65282343 0.53502448 0.39760156 0.55170929 0.54846754
17	S17	
18	S18	0.61578491 0.57098188 0.52553978 0.54603551 0.54944879
19	S19	0.4870716 0.71894418 0.60900729 0.51335682 0.51460443
20	S20	0.55395303 0.70593242 0.61716468 0.53775907 0.54677616
21	S21	0.47006416 0.46955574 0.63251422 0.51372748 0.52634127
22	S22	0.34910232 0.6478374 0.55446176 0.5162837 0.51011196
23	S23	0.31103467 0.65173626 0.40500278 0.51785624 0.52478628
24	S24	0.43642735 0.58898265 0.62447559 0.52212052 0.52469489
25	S25	0.81433122 0.81634936 0.75147713 0.55480718 0.54911735
26	S26	0.34078414 0.59796002 0.57669215 0.54078754 0.53883437
27	S27	0.76208092 0.50996532 0.62625725 0.55790885 0.55203589
28	S28	0.59237384 0.62710263 0.61936825 0.58768635 0.61098117
29	S29	0.43755633 0.59108265 0.69121309 0.55913672 0.5550338
30	S30	0.61285564 0.49010654 0.44830816 0.52757288 0.50406276
31	S31	0.78632681 0.69936215 0.57793527 0.53794 0.53822348
32	S32	0.71477973 0.70847235 0.55512262 0.53012518 0.5317325
33	S33	0.84657349 0.67064958 0.6236663 0.57997393 0.55887607
34	S34	0.66949004 0.66080105 0.65878748 0.58041147 0.57386737
35	S35	0.46466662 0.62888312 0.58861616 0.53296082 0.55063305

Figure 2: Cross-validation result :Accuracy scores for 5 folds

2 Discussion

After analyzing performance evaluation data some model has reached higher accuracy than the F1 score and this has indicated an imbalance of the data, where the model predicted all samples to be from the majority class, resulting in high accuracy but low F1 score. And Mean accuracy shows that the model performed better on some subjects than others. It can be identified the signal values do not match exactly with the outcome values stressed or not stressed. Because of that it cannot say all of the given signals are important to measure the stress and all of the subject's accuracy is more than 75% except one and the most accurate subject in figure 3 shows the stressed and not stressed values, it's false negative(FN) rate is 37.6 %.

According to the analysis of the given data it can't be said these wearable sensor data are useful to predict the stress level when considering the consistency of model performance accuracy scores. most of the data does not match the output and it is impossible to predict the importance of these signals to identify the stress.

According to my perspective about the sensor data with my analysis, there is no consistency available with the data and it changed from time to time it is not enough to measure and predict the stress of these sensor data. Because of the changes in data, developers may be faced to get an incorrect idea about stress identification and that is not a better approach to developing new features and working on a plan. It should have the best accuracy to monitor the stress with proper signals to capture the market for the new alerts generating feature in the wearable watch.

According to the literature review and some subject signals, I suggest using BVP and heart rate signals to enhance the new feature and it will be a great benefit to continue future work on the new feature. Alert generating process should be more and more accurate and stress detecting speed must be high and it should have easily detected signals to enhance new feature in a proper productive manner.

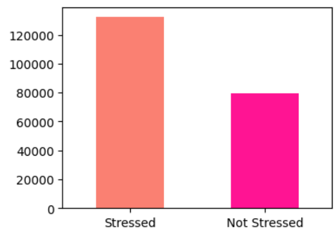

Figure 3: The most accurate subjects stress prediction

3 Conclusions

To conclude, it cannot get an accurate prediction result about the stress identification from these wearable signals data and it cannot be identified consistency of data in different signals. Performance evaluation also does not show the accurate result to identify the accuracy of the signals.

The feature importances suggest that the most important features for predicting stress are BVP (Blood Volume Pulse), EDA (Electrodermal Activity), and HR (Heart Rate), with BVP being the most important. The other features (ACC signals (X, Y, Z), and TEMP) are less important for predicting stress. But it is not the only reason to say those important features are the most valuable stress detection signals which are immediately changed when get stressed. Moreover, the number of subjects is also not enough to conclude what signals are the best to detect stress due to irrelevant signals and detecting time. When analyzing the data of some signals, some values are impossible to record under the relevant signals, and due to those reasons, I need to analyze another sample of wearable sensor data to present what signals are most important to detect stress accurately and speedily.

References

[1] T. Iqbal, A. J. Simpkin, D. Roshan, N. Glynn, J. Killilea, J. Walsh, G. Molloy, S. Ganly, H. Ryman, E. Coen, *et al.*, "Stress monitoring using wearable sensors: A pilot study and stress-predict dataset," *Sensors*, vol. 22, no. 21, p. 8135, 2022.