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Stress Detection for Wearable Devices

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ABSTRACT
In this project, Stress can be recognized by observing commute in sensitivity on the human body. The actuators which are apparel are becoming more prominent in recent years due to their functionality and discrete nature. By utilizing data from wearable sensors, we have developed a customizable stress detection system. Our system performs categorization on stress level using cross modal data from wrist-worn device Empatica E4 wearable sensor. We implemented three different classification algorithms: Logistic Regression, Decision Tree, and Random Forest and used four-class categorization conditions: baseline, stress, amusement, and meditation. By estimating the performance of the system, we exhibit that our system can perform the best and consistent customized stress detection using T-POT classifier with the accuracy of 88%-99% on 15 subjects.

KEYWORDS: Stress classification , Preprocessing , random forest ,T-POT Classifier , Wearable devices

I. INTRODUCTION

This project is titled as “Stress Detection using wearable devices”. This software provides facility to identify how the stress is detected . This project uses machine-learning methods to identify how the stress is detected. First, we use a T-pot classifer to train the dataset. Then we identify how the stress is detected. This has been developed to facilitate the identification, retrieval of the items and information. System is built with manually exclusive features. In all cases system will specify object which are physical or on performance characteristics. They are used to give optimal distraction and other information. Data are used for identifying, accessing, storing and identifying fake accounts. The data ensures that only one value of the code with a single meaning is correctly applied to give entity or attribute as described in various ways. The main features of this project are that the designer now functions as a problem solver and tries to sort out the difficulties that the enterprise faces. The solutions are given as proposals. The proposal is then weighed with the existing system analytically and the best one is selected. The proposal is presented to the user for anendorsement by the user. The proposal is reviewed on user request and suitable changes are made. This is loop that ends as soon as the user issatisfied with proposal.

II. LITERATURE REVIEW

In this section, we briefly summarize some approaches of stress detection. These approaches vary according to the various stress related factors and measures used. The measures used in this includes physical measures, physiological signals, answering questionnaire, mathematical test, videos, microblog and other techniques, etc. Also, stress detection in various environments is described below. A) Stress Detection using Wearable Sensors and IOT Devices Nowadays, sensors plays a vital role in medical applications. These are generally used for detection and measurement of various diseases and its levels. Stress is usually recognized as one of the major factors leading to various health problems. Therefore, people with high risk of getting stressed should be continuously monitored for detection of any stress signs before it causes health problems[8]. Advances in wearable sensors and mobile computing make it possible to record a variety of physical and physiological signals on a twenty-four hour basis which helps in detection of stress level. Mostly wearable sensor devices like smart band[3], Chest belts[2] are used for data collection. Some researchers used hardware and software for collection of data through sensors and detection ofstress level respectively. A Holster unit was used with LI- PO battery and PC USB Client software for detection of stress[2]. An Amulet wearable platform named StressAware was developed in [7] using SVM. This real time applications classifies the stress level of individuals by continuously monitoring HR and HRV data. Some smart bands can collect and transmit data to users smart phone via Bluetooth and even uploaded to web where it can be accessible by doctor or family members[3]. The overview of few studies are discussed which shows stressors, subjects, sensors, best accuracy achieved, the classifiers and methods used by various researchers.

III. PROPOSED DESIGN

In today's fast-paced world, mental stress is very common. Stress can be originated due to conditions or incidents such put oppression on mind and body of a person. Reaction to stress is different for everyone as the capacity of dealing with tough or demanding situations vary for person to person. Some instances might create stress to one individual, while no stress to one altogether. Also, all stress is not bad to health as it could make people more aware of things around them and keep them more cautious about dangers and focused on their goal. A stressor is an situation which creates stress to an person. Many people generally faces stress due to these stressors described in accord American Psychological Association (APA),there are mainly three types of stress which are short term tension, episodic acute tension and long term tension. Acute stress is short term stress which is least damaging type as compared to the other two. It can be good sometimes as this helps body to communicate with the event. When acute stress occurs frequently then an individual is affected with episodic acute stress. Long term stress is the most harmful type of stress, if left untreated over a long period of time can damage bodily and emotional health of a person. Long term stress puts force on the body and mind for an extended period which can create a range of indications and extend the risk of evolving certain diseases.To avoid health issues, people with high probability of feeling stressed should be continuously monitored to detect any stress signs. Wearable sensors create opportunities to monitor stress and could inform individuals regarding their stress level which can be useful in order to minimize stress balance as it results into severe health issues. Bodily health and emotional health are closely connected, hence monitoring and measuring of physiological and physical changes could be used for detecting human stress level. Stress can be detected using bodily and emotional measures of body. Bodily measures include pulse rate, skin temperature, humidity, Blood pressure and respiration rate whereas physiological measures can be heart rate, heart rate variability, skin conductance. These can be measured using wearable devices made from low-cost sensors although machine learning algorithms can be used to classify and predict stress level of an individual. In this paper, some previous approaches of automatic stress recognition systems who used sensors and machine learning are discussed in detail. In these, emotional data is extracted using some stressor tests on the people. Some common stressor tests includes arithmetic calculations, questionnaire, mental tasks and working out in gym. There are a diversity of machine learning algorithms which are appropriate for stress detection. Among them Support Vector Machines (SVM), Logistic regression, K-Nearest Neighbor, Decision tree and Random forest are most common. In this review, we summarize the various machine learning algorithms available in the writings thataim at perceiving state of stress.

3.1 PROPOSED SYSTEM

In this paper, some previous approaches of automatic stress identification systems who used sensors and also machine learning are discussed in detail. In these, physiological data is extracted using some stressor tests on the people. Some common stressor tests includes arithmetic calculations, questionnaire, mental tasks and working out in gym. There are a diversity of machine learning algorithms which are appropriate in stress detection. Among them Support Vector Machines (SVM), Logistic regression, KNearest Neighbor, Decision tree and Random forest are most common. In this review, we summarize the various machine learning algorithms present in the literature that aim at detecting state of stress.

3.2 PROJECT ARCHITECTURE

The dataset is collected from the sensor based devices like smart phones and smart watches.The collected data is preprocessed with the features we'd like. Here we use T-pot automated classifier to classify the information. TPOT is supposed to be an assistant that provides you ideas on the way to solve a selected machine learning problem by exploring pipeline configurations that you simply may need never considered, then leaves the fine- tuning to more constrained parameter tuning techniques like grid search. TPOT is made on the scikit learn library and follows the scikit learn API closely. It may be used forregression and classification tasks and has special implementations for medical research.TPOT is open source, well documented, and under active development. TPOT has what its developers call a genetic search algorithm to seek out the most effective parameters and model ensembles. It could even be thought of as a selection or evolutionary algorithm. TPOT

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tries a pipeline, evaluates its performance, and randomly changes parts of the pipeline in search of higher performing algorithms.

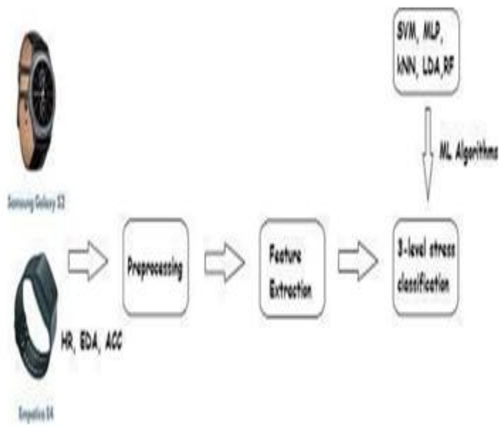
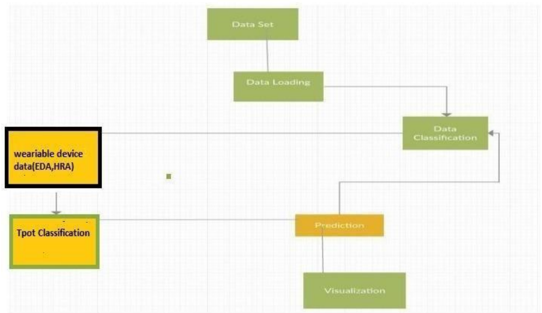


Fig 1. Architecture of stress detection

3.3 DATA FLOW DIAGRAM




```
selected_x_columns = ['HR', 'RMSSD', 'pNN50', 'TP', 'VLF', 'LF', 'HF','LF_HF']
X = dataframe_hrv[selected_x_columns]
display(X.head(5))
```

	HR	RMSSD	pNN50	TP	VLF	LF	HF	LF_HF
0	69.499952	15.554505	0.533333	3686.666157	2661.894136	1009.249419	15.522603	65.018055
1	64.363150	12.964439	0.000000	3006.487251	2314.265450	690.113275	2.108525	327.296635
2	67.450066	16.305279	0.200000	2685.879461	1373.887112	1298.222619	13.769729	94.280910
3	68.809562	15.720468	0.133333	3434.520980	2410.357408	1005.981659	18.181913	55.328701
4	74.565728	19.213819	0.200000	2621.175204	1151.177330	1421.782051	48.215822	29.487873

Fig 2. Dataflow diagram of stress detection

IV. RESULTS AND DISCUSSION

```
from sklearn.model_selection import train_test_split
from sklearn.neural_network import MLPClassifier
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import GridSearchCV
from tpot import TPOTClassifier
%matplotlib inline
import matplotlib.pyplot as plt
from scipy import signal
import pickle


import sklearn.metrics
from sklearn.model_selection import cross_val_score
from sklearn import svm
import numpy as np
import pandas as pd
from sklearn.metrics import precision_recall_fscore_support

pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
pd.set_option('display.max_colwidth', -1)
dataframe_hrv = pd.read_csv("hrv dataset/hrv dataset/data/final/train.csv")
dataframe_hrv = dataframe_hrv.reset_index(drop=True)
display(dataframe_hrv.head(5))
```

```
C:\Users\home\anaconda3\lib\site-packages\tpot\builtins\__init__.py:36: UserWarning: Warning: optional dependency `torch` is no
t available. - skipping import of NN models.
  warnings.warn("Warning: optional dependency `torch` is not available. - skipping import of NN models.")
<ipython-input-1-adecb2093410>:118: FutureWarning: Passing a negative integer is deprecated in version 1.0 and will not be supp
orted in future version. Instead, use None to not limit the column width.
  pd.set_option('display.max_colwidth', -1)
```

	MEAN_RR	MEDIAN_RR	SDRR	RMSSD	SDSD	SDRR_RMSSD	HR	pNN25	pNN50	SD1	SD2	KURT	SKEW	ME
0	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
1	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
2	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
4	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Fig 3. Importing the dataset

In the above figure 3,the dataset is imported from various devices such as kaggle datasets and smart devices.

```
def fix_stress_labels(df='',label_column='condition'):
    df['condition'] = np.where(df['condition']=='no stress', 0, 1)
    display(df["condition"].unique())
    return df
dataframe_hrv = fix_stress_labels(df=dataframe_hrv)
Y = dataframe_hrv['condition']
display(Y.head(5))
```

```
array([0, 1])

0    0
1    1
2    1
3    0
4    0
Name: condition, dtype: int32
```

Fig 4. Condition statement for stress detection

```
selected_x_columns = ['HR', 'RMSSD', 'pNN50', 'TP', 'VLF', 'LF', 'HF','LF_HF']
X = dataframe_hrv[selected_x_columns]
display(X.head(5))
```

	HR	RMSSD	pNN50	TP	VLF	LF	HF	LF_HF
0	69.499952	15.554505	0.533333	3686.666157	2661.894136	1009.249419	15.522603	65.018055
1	64.363150	12.964439	0.000000	3006.487251	2314.265450	690.113275	2.108525	327.296635
2	67.450066	16.305279	0.200000	2685.879461	1373.887112	1298.222619	13.769729	94.280910
3	68.809562	15.720468	0.133333	3434.520980	2410.357408	1005.981659	18.181913	55.328701
4	74.565728	19.213819	0.200000	2621.175204	1151.177330	1421.782051	48.215822	29.487873

Fig 5. Inserting columns needed for stress detection

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```
newDataframe_hrv = pd.read_csv("hrv dataset/hrv dataset/data/final/test.csv")
newdataframe_hrv = dataframe_hrv.reset_index(drop=True)
new_selected_x_columns = ['HR', 'RMSSD', 'pNN50', 'TP', 'VLF', 'LF', 'HF','LF_HF']
newX = newDataframe_hrv[selected_x_columns]
display(newX.head(5))
```

	HR	RMSSD	pNN50	TP	VLF	LF	HF	LF_HF
0	84.121868	12.361264	0.000000	1698.605390	1016.073759	615.914573	66.617057	9.245599
1	71.478642	19.298880	0.200000	2358.884694	765.518473	1566.866135	26.500086	59.126832
2	63.874293	21.342715	1.800000	4328.633724	2237.739905	2074.868884	16.024935	129.477524
3	74.330531	11.771814	0.533333	2854.449091	2330.980957	505.886664	17.581470	28.773854
4	82.092049	13.357748	0.666667	5310.027472	4750.624447	524.203971	35.199054	14.892559

Fig 6. Assigning the minimum values

```
def do_tpot(generations=5, population_size=10,X='',y=''):

    X_train, X_test, y_train, y_test = train_test_split(X, y,train_size=0.80,test_size=0.20)
    tpot = TPOTClassifier(generations=generations, population_size=population_size, verbosity=2,cv=3)
    tpot.fit(X_train, y_train)
    print(tpot.score(X_test, y_test))
    tpot.export('tpot_pipeline.py')
    return tpot

tpot_classifer = do_tpot(generations=5, population_size=20,X=X,y=Y)
```

```
Generation 1 - Current best internal CV score: 0.9999593813783929
Generation 2 - Current best internal CV score: 0.9999593813783929
Generation 3 - Current best internal CV score: 0.9999593813783929
Generation 4 - Current best internal CV score: 0.9999593813783929
Generation 5 - Current best internal CV score: 0.9999661511488687

Best pipeline: ExtraTreesClassifier(ZeroCount(input_matrix), bootstrap=False, criterion=entropy, max_features=0.8, min_samples_
leaf=3, min_samples_split=2, n_estimators=100)
0.9999864805052939
```

Fig 7. Values of cv scores

```
display(newDataframe_hrv['condition'].head(5))
```

```
0    no stress
1    time pressure
2    no stress
3    no stress
4    interruption
Name: condition, dtype: object
```

Fig 8. Condition values for stress detection

```
pred = tpot_classifer.predict_proba(newX)
dfpred = pd.DataFrame(pred)
display(dfpred.head(5))
```

	0	1
0	1.00000	0.00000
1	0.00000	1.00000
2	1.00000	0.00000
3	0.99993	0.00007
4	0.05469	0.94531

Fig 9. Output in binary variables format

V. CONCLUSION

We developed a stress detection scheme to beutilized in real world.We have collected different parametric values of heart beat from smart watches and obtained the strain resullts. We achieved maximum 97.92% accuracy for three-level stress detection. the most effective performing classifiers were the Random Forest and also the Multilayer Perceptron algorithms. classification accuracy, whereas this was 86.27% when these modalities were used separately. Finally, we observed that the perceived stress level classification leads to lower accuracies than physiological stress level classification. there have been up to fifteen decrease in comparison with physiological stress level classification accuracies.

VI. ACKNOWLEDGMENT

The success of this project includes help from our guide as well.We are grateful to our guide,Mrs.D.Sandhya Rani,Assistant Professor,CMR Technical Campus,for her expertise that guided us in our reasearch.

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