Wearable Device for Detecting Depression

Data Analysis

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I. Background and Purpose of Research

Depression is a major problem in our society. It is a medical condition that affects the way people think and behave, as well as the way people feel and function. It is one of the most common mental health problems and is faced by over 121 million people worldwide. In Singapore, an estimated 5.6% of the population is affected by depression during their lifetime. [1] People with depression experience severe and prolonged feelings of negative emotions like sadness, anger, disgust and fear. The purpose of this research is to detect persistent negative emotions for detection of depression, using a detecting device that is connected to four physiological sensors. Early detection of depression allows medical attention to be given to patients earlier, for appropriate treatment to be provided to them.

II. Hypothesis

A device that is trained with a classifier is able to detect depression by identifying the emotion that the person is feeling. By closely monitoring the person's emotions over two weeks, the device is able to show whether the person has been suffering from prolonged feelings of negative emotions for depression to be detected.

III. Data Analysis

A. Methods and Materials

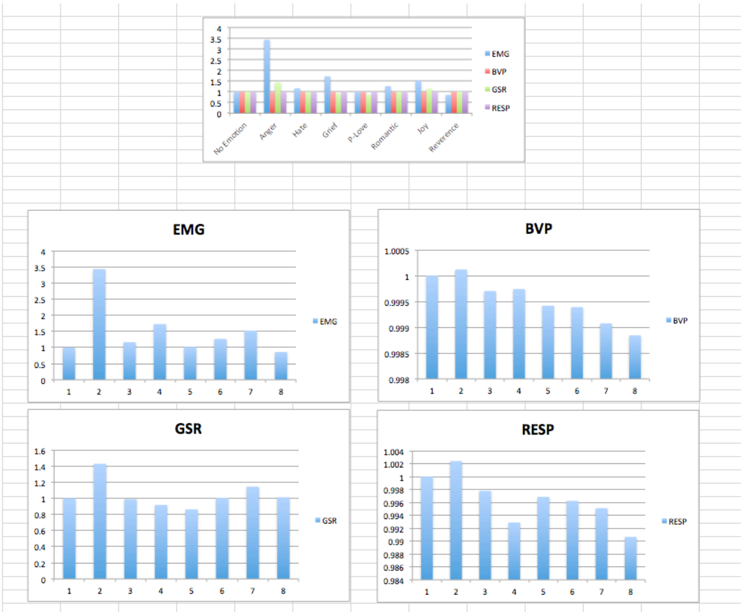
Materials: Data provided by Massachusetts Institute of Technology (MIT)

A person selects eight different images that will cause him to feel eight different emotions: No Emotion, Anger, Hate, Grief, Platonic Love, Romantic Love, Joy and Reverence. The emotions of the person are tracked by connecting four sensors to the person, over 20 days. These four sensors are responsible for tracking four different physiological signals, namely masseter muscle contractions (EMG), blood volume pressure (BVP), skin conductance (GSR) and respiratory rate (RESP). These sensors are able to provide data, which will be used for training of the program and for future predictions. If the program is able to detect that a person has been suffering from negative emotions for a long period of two weeks (14 days), the device is successful in detecting depression early. [2] The data provided has four columns for the four different sensors. For each sensor, the data is subdivided into eight columns, for the eight different emotions the person experienced. For each of the 20 days, there are 2001 rows of data.

Method: Creating the Device

Using Python, a program is created. In this program, the data provided by MIT is used. For each emotion of each sensor over the 20 days, the program calculates the mean. This is for data plotting using Excel, for a trend to be observed to find out whether it is possible for the device to be trained to identify a particular emotion, when provided with data from the four sensors.

B. Results and Discussions



The bar graphs show the trend for the four different signals. For each signal, the eight emotions, No Emotion, Anger, Hate, Grief, Platonic Love, Romantic Love, Joy and Reverence are represented by the numbers 1, 2, 3, 4, 5, 6, 7 and 8 respectively. All data has been normalized to EMG No Emotion. Hence, EMG No Emotion has a value of 1. As shown by the bar graph for EMG, the data value for Anger is significantly higher than those for all the other emotions. For the bar graphs for BVP, GSR and RESP, the data values for anger are also the highest, as compared that of the other emotions. This shows that the device can be trained to identify anger, which is a strong negative emotion, for depression to be detected if the emotion persists over two weeks (14 days). However, other negative emotions, namely anger, hate and grief, do not result in higher data values collected from the sensors than the positive emotions, Platonic Love, Romantic Love, Joy and Reverence. These negative emotions also do not generate data values that are significantly higher than that generated by the neutral emotion, No Emotion. This makes it difficult for the device to be tracking the emotions a person has been experiencing over two weeks. Therefore, after discussion with my mentor, it will be better for the device to identify positive, neutral and negative emotions, instead of specific emotions, No Emotion, Anger, Hate, Grief, Platonic Love, Romantic Love, Joy and Reverence.

IV. MACHINE-LEARNING

A. *Methods and Materials*

Using scikit-learn for Machine Learning in Python, train the device in four steps:

1. Import Library (from sklearn import svm)
2. Create a Classifier (clf = svm.SVC(kernel=’linear’)
3. Train the Classifier (clf.fit(data,target))
4. Predict New Data (clf.predict(0.21))

Step 1 imports the module svm. Step 2 creates a linear classifier. A linear classifier is a line of best fit that the program draws based on the raw data provided by MIT. This linear classifier allows the program to identify the emotion when four data, for the four sensors, EMG, BVP, GSR and RESP respectively, are provided. Step 3 fits the data with the target. In this case, Step 3 is fitting emodata with lbl, the final label created by combining all the individual labels for all the individual emotions of the four sensors. Step 4 enables new data to be predicted, using the created classifier. [3]

Training of Device to Detect Depression:

```
from emodata import *
from sklearn import svm
fnoEmo='NoEmotion.csv'
fanger='Anger.csv'
fhate='Hate.csv'
fgrief='Grief.csv'
fpLove='PlatonicLove.csv'
frLove='RomanticLove.csv'
fjoy='Joy.csv'
freverence='Reverence.csv'
feature_list=['EMG','BVP','GSR','RESP']
noEmo=EmoData()
noEmo.load(fnoEmo, feature_list)
lblNoEmo=['NoEmotion' for i in range(noEmo.n_samples)]
anger=EmoData()
anger.load(fanger, feature_list)
lblAnger=['Anger' for i in range(anger.n_samples)]
hate=EmoData()
hate.load(fhate, feature_list)
lblHate=['Hate' for i in range(hate.n_samples)]
grief=EmoData()
grief.load(fgrief, feature_list)
lblGrief=['Grief' for i in range(grief.n_samples)]
pLove=EmoData()
pLove.load(fpLove, feature_list)
lblPlatonicLove=['PlatonicLove' for i in range(pLove.n_samples)]
rLove=EmoData()
rLove.load(frLove, feature_list)
lblRomanticLove=['RomanticLove' for i in range(rLove.n_samples)]
joy=EmoData()
joy.load(fjoy, feature_list)
lblJoy=['Joy' for i in range(joy.n_samples)]
reverence=EmoData()
reverence.load(freverence, feature_list)
lblReverence=['Reverence' for i in range(reverence.n_samples)]
lbl=lblNoEmo+lblAnger+lblHate+lblGrief+lblPlatonicLove+lblRomanticLove+lblJoy+lblReverenc
lbl=np.array(lbl)
emo=noEmo
emo.concat(anger)
emo.concat(hate)
```

```
emo.concat(grief)
emo.concat(pLove)
emo.concat(rLove)
emo.concat(joy)
emo.concat(reverence)
clf=svm.SVC()
clf.fit(emo.data ,lbl)
```

B. *Results and Discussions*

The program took a very long time to run the data because the data was extremely huge. However, the program only needs to run the data once as this running of data can be saved for future predictions to be carried out quickly. This enables faster identification of emotions and thereby allowing faster detection of depression.

The values, 5.95, 33.08, 5.41 and 46, which are a set of data values for anger from the four sensors, are used for prediction. The program is successful in identifying the emotion, ‘Anger’. However, this set of data is a set of data from the huge amount of data used in training the classifier. Therefore, a set of new data has yet to be used for detection of emotion by the program.

However, having used all the data to draw the classifier, there is now insufficient data for prediction. Thus, the data has to be split into two.

V. Separation of Data

A. Methods and Materials

The data has been split into two: 60% of the data will be used to train the classifier whereas 40% of the data will be used for prediction.

New Program Classifier:

```
#clf=svm.SVC()
#clf.fit(emo.data ,lbl)
#new=[5.95, 33.08, 5.41, 46]
#new=np.array(new)
#print clf.predict(new)
#print emo.n_samples
x_train, x_test, y_train, y_test=cross_validation.train_test_split(emo.data,lbl,test_size=0.4,random_state=0)
print x_train.shape, y_train.shape
print x_test.shape, y_test.shape
clf=svm.SVC()
clf.fit(x_train,y_train)
joblib.dump(clf, 'model2.pkl')
clf.score(x_test,y_test)
```

B. Results and Discussions

The data is run to the end and the score of prediction (in %) received is 58.48%. This score of prediction is too low for accurate prediction of the emotion a person is feeling. One reason behind this low score of prediction could be because of the splitting of the data into two, which might have resulted in insufficient data to draw an accurate classifier. Another reason could be due to the similarity of data between emotions, making it too difficult for the program to accurately identify the emotion. Possible ways to increase score of prediction:

1. Try increasing the value of c (default value of c: 1.0)
2. Try different gamma parameter
3. Try using only three classes: Positive, Neutral and Negative Emotions
4. Try increasing percentage (number) of data used to train classifier
5. Try different features such as trying to use the difference between two data

VI. Improving Fit of Classifier

A. Methods and Materials

Change the value of c to create a more complex model, and that is, a less linear and curvier classifier. This classifier is more accurate as it is closer to the raw data provided by MIT.
Parameters used: Default
Clf=svm.SV(c)
c=1.0
kernel=rbf
degree=3
gamma='auto'
1/nfeatures=1/4=0.25
Run for different values of c, c=10, c=100, c=1000.

B. Results and Discussions

Value of c	Score of Prediction/%	Improvement/%
1	58.48	-
10	62.52	4.04
100	64.45	1.93
1000	64.45	0

When we run for different values of c, the score of prediction increases but at a decreasing rate, coming to a plateau from c=100 onwards, with a score of 64.45%.
This score of prediction shows that the device is not accurate enough to detect depression well.

VII. Re-categorisation of Emotions

A. Methods and Materials

Since the data is too close for the eight different emotions, experiment is now run labeling only with three classes: 'Positive', 'Neutral' and 'Negative'. 'Positive' includes Platonic Love, Romantic Love, Joy and Reverence. 'Neutral' includes No Emotion. 'Negative' includes Anger, Hate and Grief. Secondly, the value of c is increased.

B. Results and Discussions

Value of c	Score of Prediction/%	Improvement/%
1	73.09	14.61
10	74.89	1.8
100	75.72	0.83

When the eight emotions are categorized into three categories: Positive, Neutral, Negative, the score of prediction increased very greatly, from 58.48% to 73.09%. The increase is 14.61%. By increasing the value of c, the score of prediction increased further, reaching a final score of prediction of 75.72% when c=100. This high score of prediction shows that the device is very likely to detect depression accurately.

RECOMMENDATIONS FOR FUTURE WORK

The accuracy of prediction can be increased via three ways. Firstly, cross-validation can be used such that rather than splitting the data, all the data is used. With a larger amount of data available for training of the program, a more accurate classifier can be created for more accurate detection of depression. Secondly, different features such as by using the standard deviations for the eight different emotions can be tried. Thirdly, different gamma parameter can be tried. By increasing gamma, the prediction zone of each data value becomes smaller. With less global and more local zones, prediction will be more accurate and thus the detection of depression will be more accurate.

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