# Emotion detection through smartphone typing

by

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May, 2019

## Declaration

I hereby declare that

(i) the project comprises of my original work towards the degree of Master of Technology in Information and Communication Technology at DA-IICT and has not been submitted elsewhere for a degree,

(ii) due acknowledgement has been made in the text to all the reference material used.

Maniar Shailja

## Certificate

This is to certify that the project work entitled Emotion detection through smartphone typing has been carried out by Maniar Shailja (201711060) for the degree of Master of Technology in Information and Communication Technology at Dhirubhai Ambani Institute of Information and Communication Technology under my supervision.

Prof. Kalyan Sasidhar

Project Supervisor

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## Abstract

Keystroke analysis or typing analysis for detecting human emotion refers to the method of recognizing emotion based on the typing pattern by checking the various features like typing speed, typing mistakes, usage of special characters, number of sessions, number of characters in a session, number of words etc. This approach can be considered desirable in human computer interaction because the data used is rather non-intrusive and easy to obtain. However, there were only limited investigations about the phenomenon itself in previous studies. This work aims to examine the source of variance in keystroke typing patterns caused by emotions. As it is smartphone typing based emotion detection, first I have designed a custom keyboard in android which can collect these typing pattern features. Then to get these typing data in csv file for feature extraction firebase analytics cloud service is used. Along with typing data self-reported emotion states (happy, sad, excited, stressed) are also collected. After that in python various features are extracted to train multiclass classification model Like decision tree, random forest, K-Nearest Neighbors. The experiment is performed on three different users. Here physiological, psychological and behavioural modalities are combined that is to check whether using heartrate along with typing data improves the accuracy or not two user's heartrate data along with typing data is collected and then compared. As collected emotion classes are imbalanced, to check the accuracy precision, recall and f1 score are measured. The result shows that using heartrate along with typing data increases the accuracy for emotion detection. The result also shows that emotional influence on keystroke pattern changes based on person's characteristic. So, by this way, this work is a small step towards answering the question that how strongly is smartphone typing correlated to our perceived emotion.

# List of Principal Acronyms

| | |
|---|---|
| CH | Number of characters |
| DEL | Number of delete key pressed |
| SP | Number of special characters typed |
| HR | Heartrate |
| SESSIONS | Number of typing sessions |
| mfsi | Mean fraction of 3 seconds inter tap distance |
| Class 1 | Happy |
| Class 2 | Sleepy |
| Class 3 | Excited |
| Class 4 | Stressed |

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# Chapter 1

# Introduction

## 1.1 General

- In Affective Computing, emotions are detected using different modalities, such as speech, facial expressions, physiological properties etc.
- The advantage of using keystroke analysis for detecting human emotion is its reliability, low resource overhead, non-intrusiveness that is no additional devices need to be purchased or integrated.
- Now a days, we use several applications on smartphones which are based on typing. Moreover, these typing based applications are often conversational in nature, especially communication applications.
- As smartphones proliferate, this study aimed to examine the source of variance in keyboard typing patterns caused by emotions.
- The idea behind keystroke dynamics is that people have different typing styles and by analysing keyboard typing patterns like timings of keystroke, number of characters typed, number of words, number of special characters, number of delete key pressed, number of sessions, emotions can be identified correctly or not.
- So, the motive behind this idea is if we could develop an intelligent system which can interact with human involving emotions, that is, it can detect user emotions and change its behaviour accordingly, then using machines could be more effective and friendly.
- In this work, a personalized multi emotion prediction model is developed that takes various typing features as an input and predicts the emotion. Emotion accuracy is compared with self-reported emotions.

## 1.2 Organisation of the Report

- Chapter 1 includes introduction and motivation behind this idea. It includes what is typing based emotion detection and why we need to use it.
- Chapter 2 includes data collection and pre-processing. It includes how typing pattern data is collected using custom keyboard which is made in android. Also, it talks about firebase cloud service to store typing pattern data. In addition to this it includes impact of heartrate on emotion, data pre-processing and feature extraction in python.
- Chapter 3 includes three types of classification algorithm performed on three different users. The classification algorithms are decision tree, KNN, random forest. It also includes different results and plots generated by classification algorithms.
- Chapter 4 includes discussion about experiment that is performed on three different users and conclusion of the experiment and future scope.

# Chapter 2

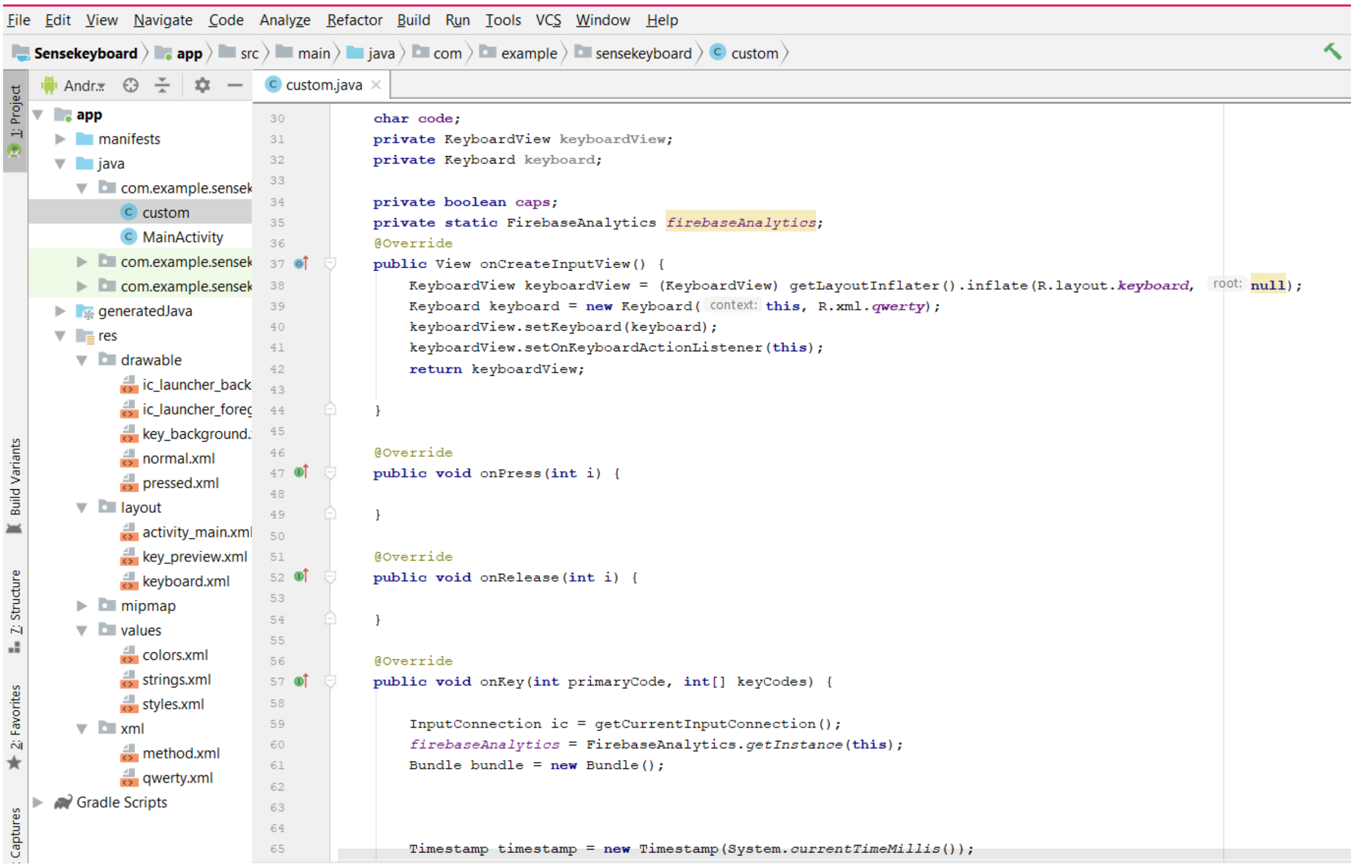
# Data Collection and Pre-processing

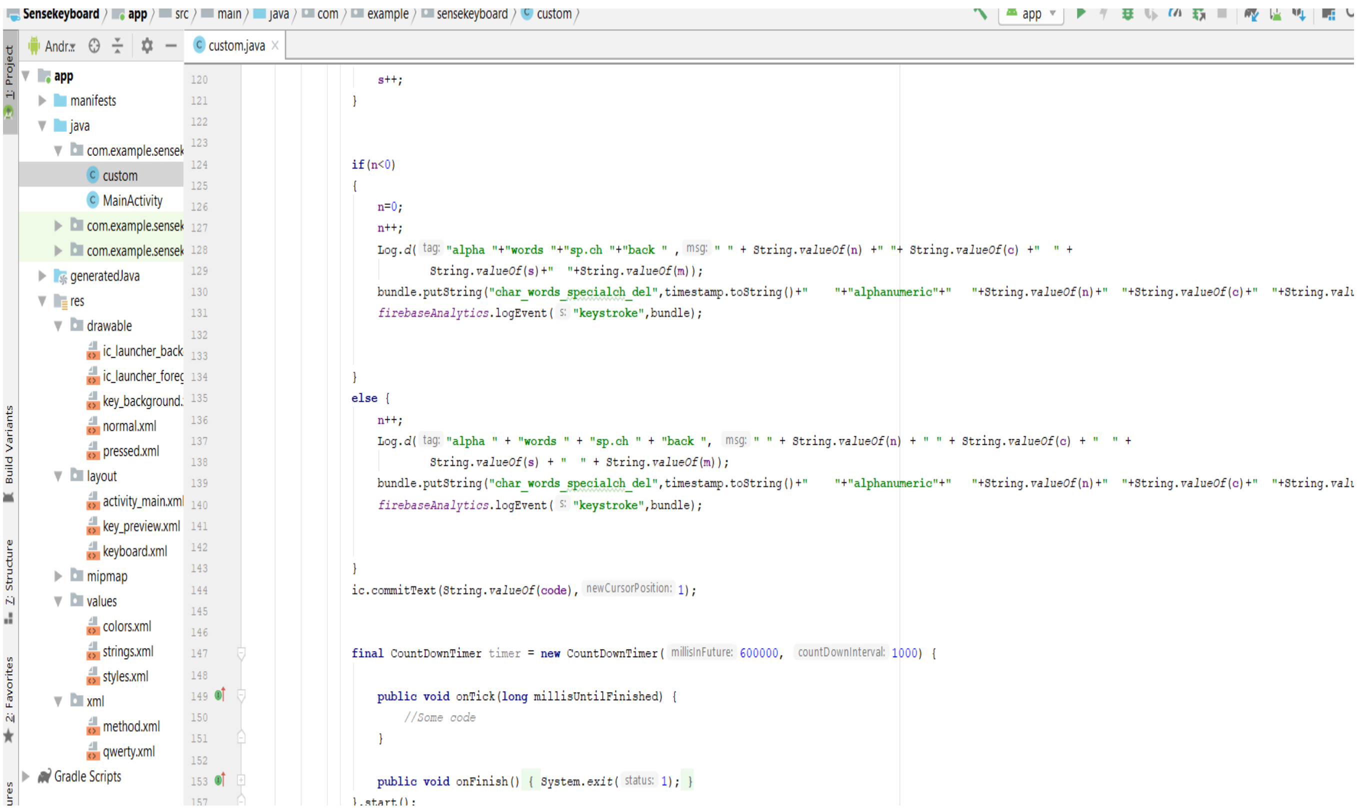
## 2.1 Custom keyboard development

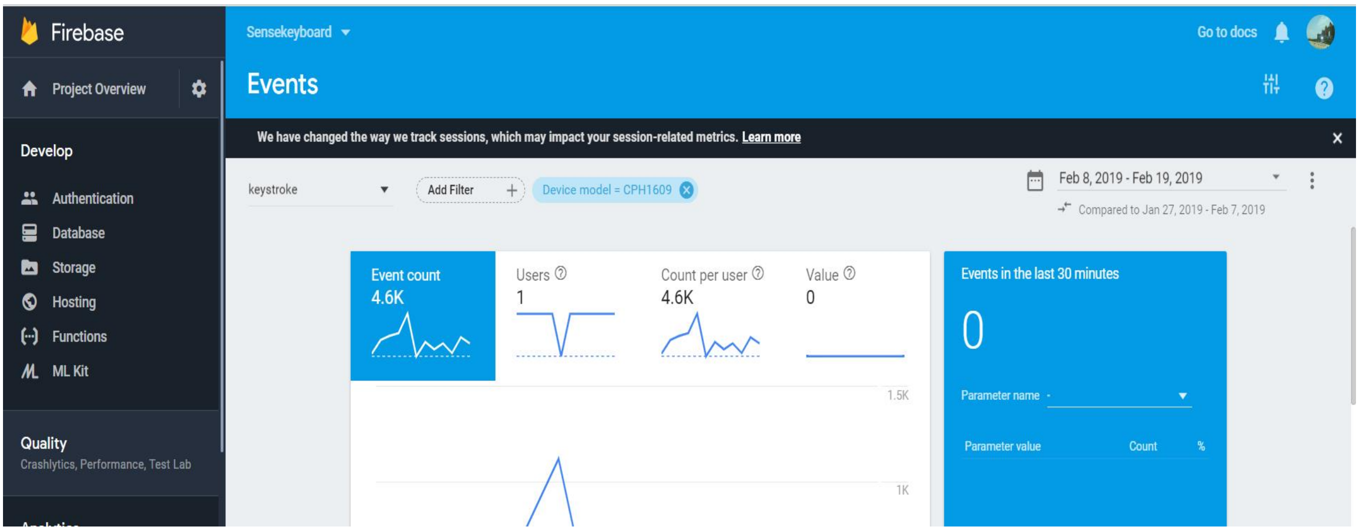
- First, to collect typing pattern data I have designed an android based custom keyboard named as Sensekeyboard and installed it in mobile.
- In the keyboard I have implemented the code that can collect timing of each key pressed, type of key (alphanumeric or delete), number of characters, words, special characters and number of delete key.
- To ensure user privacy what user have typed is not collected.
- Then in my code I have included firebase analytics cloud service and generated custom event keystroke that stores typing pattern data.
- So, whoever user installs the keyboard, I can get that users typing data in csv file directly from the cloud i.e. firebase analytics. So, no additional hardware is required to collect user's data. Below is the glimpse of code.

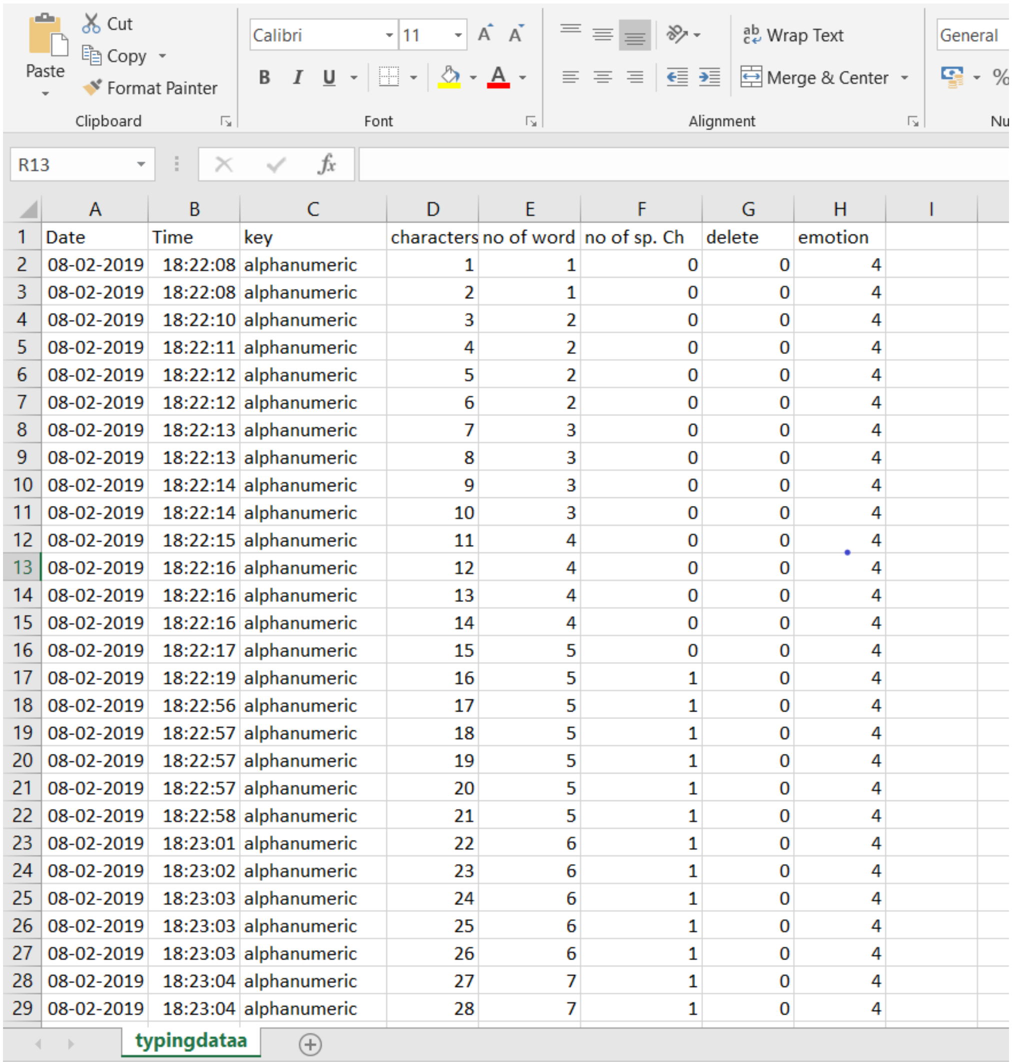
### Keyboard look:


### Glimpse of keyboard generation code and csv file containing raw data:


char code;
private KeyboardView keyboardView;
private Keyboard keyboard;
private boolean caps;
private static FirebaseAnalytics firebaseAnalytics;
@Override
public View onCreateInputView() {
KeyboardView keyboardView = (KeyboardView) getLayoutInflater().inflate(R.layout.keyboard, root: null);
Keyboard keyboard = new Keyboard( context: this, R.xml.qwerty);
keyboardView.setKeyboard(keyboard);
keyboardView.setOnKeyboardActionListener(this);
return keyboardView;
}
@Override
public void onPress(int i) {
}
@Override
public void onRelease(int i) {
}
@Override
public void onKey(int primaryCode, int[] keyCodes) {
InputConnection ic = getCurrentInputConnection();
firebaseAnalytics = FirebaseAnalytics.getInstance(this);
Bundle bundle = new Bundle();
Timestamp timestamp = new Timestamp(System.currentTimeMillis());


s++;
}
if(n<0)
{
n=0;
n++;
Log.d( tag: "alpha "+"words "+"sp.ch "+"back " , msg: " " + String.valueOf(n) +" "+ String.valueOf(c) +" " +
String.valueOf(s)+" "+String.valueOf(m));
bundle.putString("char_words_specialch_del",timestamp.toString()+" "+"alphanumeric"+" "+String.valueOf(n)+" "+String.valueOf(c)+" "+String.valu
firebaseAnalytics.logEvent( s: "keystroke",bundle);
}
else {
n++;
Log.d( tag: "alpha " + "words " + "sp.ch " + "back ", msg: " " + String.valueOf(n) + " " + String.valueOf(c) + " " +
String.valueOf(s) + " " + String.valueOf(m));
bundle.putString("char_words_specialch_del",timestamp.toString()+" "+"alphanumeric"+" "+String.valueOf(n)+" "+String.valueOf(c)+" "+String.valu
firebaseAnalytics.logEvent( s: "keystroke",bundle);
}
ic.commitText(String.valueOf(code), newCursorPosition: 1);
final CountDownTimer timer = new CountDownTimer( millisInFuture: 600000, countDownInterval: 1000) {
public void onTick(long millisUntilFinished) {
//Some code
}
public void onFinish() { System.exit( status: 1); }
}.start();




| | A | B | C | D | E | F | G | H |
|---|---|---|---|---|---|---|---|---|
| 1 | Date | Time | key | characters | no of word | no of sp. Ch | delete | emotion |
| 2 | 08-02-2019 | 18:22:08 | alphanumeric | 1 | 1 | 0 | 0 | 4 |
| 3 | 08-02-2019 | 18:22:08 | alphanumeric | 2 | 1 | 0 | 0 | 4 |
| 4 | 08-02-2019 | 18:22:10 | alphanumeric | 3 | 2 | 0 | 0 | 4 |
| 5 | 08-02-2019 | 18:22:11 | alphanumeric | 4 | 2 | 0 | 0 | 4 |
| 6 | 08-02-2019 | 18:22:12 | alphanumeric | 5 | 2 | 0 | 0 | 4 |
| 7 | 08-02-2019 | 18:22:12 | alphanumeric | 6 | 2 | 0 | 0 | 4 |
| 8 | 08-02-2019 | 18:22:13 | alphanumeric | 7 | 3 | 0 | 0 | 4 |
| 9 | 08-02-2019 | 18:22:13 | alphanumeric | 8 | 3 | 0 | 0 | 4 |
| 10 | 08-02-2019 | 18:22:14 | alphanumeric | 9 | 3 | 0 | 0 | 4 |
| 11 | 08-02-2019 | 18:22:14 | alphanumeric | 10 | 3 | 0 | 0 | 4 |
| 12 | 08-02-2019 | 18:22:15 | alphanumeric | 11 | 4 | 0 | 0 | 4 |
| 13 | 08-02-2019 | 18:22:16 | alphanumeric | 12 | 4 | 0 | 0 | 4 |
| 14 | 08-02-2019 | 18:22:16 | alphanumeric | 13 | 4 | 0 | 0 | 4 |
| 15 | 08-02-2019 | 18:22:16 | alphanumeric | 14 | 4 | 0 | 0 | 4 |
| 16 | 08-02-2019 | 18:22:17 | alphanumeric | 15 | 5 | 0 | 0 | 4 |
| 17 | 08-02-2019 | 18:22:19 | alphanumeric | 16 | 5 | 1 | 0 | 4 |
| 18 | 08-02-2019 | 18:22:56 | alphanumeric | 17 | 5 | 1 | 0 | 4 |
| 19 | 08-02-2019 | 18:22:57 | alphanumeric | 18 | 5 | 1 | 0 | 4 |
| 20 | 08-02-2019 | 18:22:57 | alphanumeric | 19 | 5 | 1 | 0 | 4 |
| 21 | 08-02-2019 | 18:22:57 | alphanumeric | 20 | 5 | 1 | 0 | 4 |
| 22 | 08-02-2019 | 18:22:58 | alphanumeric | 21 | 5 | 1 | 0 | 4 |
| 23 | 08-02-2019 | 18:23:01 | alphanumeric | 22 | 6 | 1 | 0 | 4 |
| 24 | 08-02-2019 | 18:23:02 | alphanumeric | 23 | 6 | 1 | 0 | 4 |
| 25 | 08-02-2019 | 18:23:03 | alphanumeric | 24 | 6 | 1 | 0 | 4 |
| 26 | 08-02-2019 | 18:23:03 | alphanumeric | 25 | 6 | 1 | 0 | 4 |
| 27 | 08-02-2019 | 18:23:03 | alphanumeric | 26 | 6 | 1 | 0 | 4 |
| 28 | 08-02-2019 | 18:23:04 | alphanumeric | 27 | 7 | 1 | 0 | 4 |
| 29 | 08-02-2019 | 18:23:04 | alphanumeric | 28 | 7 | 1 | 0 | 4 |

- I have included count down timer for 10 mins in my code. So, suppose a user starts using keyboard at that time this count down timer will be started and if user has not stopped typing after 10 mins a new session will be started.
- New session means counter of characters, words, special characters and delete key will start from 0 again.
- The three different user's data is collected to perform the experiment.
- Total 4 emotion states i.e. happy (1), sad (2), excited (3), stressed (4) are recorded using self-reports.
- First user is me; I have collected my typing data of 2 weeks which have around 6000 typing records. Second user and third user's typing data is of 1 week.
- Data pre-processing includes eliminating small sessions (less than 5 typing events), normalization and removing the missing values.

## 2.2 Feature Extraction

- Feature extraction is done in python.
- Inter Tap Distance: time taken between two consecutive keypress events. Suppose at 10:05:08 alphanumeric key is pressed and next alphanumeric key is pressed at 10:05:10 then inter tap distance between these two is 2.0 seconds.
- Number of sessions in a day: As mentioned above, when user starts using keyboard at that time count down timer will be started. After 10 mins there will be a new session. For new session counter for typing events will start from 0 again. So, it is defined as when character typed is 1 and delete key is 0 at that time there will be a new session.
- Now the next thing is when there is a new session as we can see in below picture after the record 505, at 506 new session starts. So, at that time inter tap distance between two keys i.e. for 505 and 506 inter tap distance should be 0 as they are not two consecutive keypress events.

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 502 | 09-02-2019 | 15:59:04 | alphanumeric | 58 | 13 | 3 | 4 | 3 |
| 503 | 09-02-2019 | 15:59:04 | alphanumeric | 59 | 13 | 4 | 4 | 3 |
| 504 | 09-02-2019 | 15:59:05 | delete | 58 | 13 | 4 | 5 | 3 |
| 505 | 09-02-2019 | 15:59:05 | alphanumeric | 59 | 13 | 5 | 5 | 3 |
| 506 | 09-02-2019 | 17:58:18 | alphanumeric | 1 | 1 | 0 | 0 | 3 |
| 507 | 09-02-2019 | 17:58:19 | alphanumeric | 2 | 1 | 0 | 0 | 3 |
| 508 | 09-02-2019 | 17:58:19 | alphanumeric | 3 | 2 | 0 | 0 | 3 |

- Mean of number of characters, words, special characters and number of delete key, number of sessions at every 3 seconds.
- To get the answer of the questions like does heartrate change with what kind of work we do? Especially when we are typing? Does it have emotional influence? The experiment is performed on second and third user's typing data along with heartrate data. And then emotion accuracy is compared with only typing features and typing feature with heartrate.
- The extracted features are then given in another csv file. The glimpse of python code for feature extraction is shown below.

```
import pandas as pd
data=pd.read_csv(r"C:\Users\shail\Documents\device a6000\itd.csv")

data['Time'] = pd.to_timedelta(data['Time'])

#Inter tap distance
data['sec']=data['Time'].diff().dt.total_seconds()

#Inter tap distance when new session
data.loc[(data['characters'] == 1) & (data['delete'] == 0) , 'sec'] = 0

print(data['sec'])

#no of sessions
m=0

for a, b in zip(data.characters,data.delete):

        if a==1 and b==0 :

            m=m+1

            print m

        else:

            print m


pd.set_option('display.max_rows',800)

#mean of ITD, no of..

data.set_index(data['Time'],inplace=True)

print(data[['characters','no of word','no of sp. Ch','delete','heartrate','no of sessions']].resample("3S").mea
print(data[['sec']].resample("3S").mean().dropna())
```

# Chapter 3

# Experiments and Results

## User 1:

- From my own typing data (6500 records) after feature extraction 70% data is used for training while 30% data is used for testing.
- Various classification techniques used for multiclass classification. Decision tree classification accuracy (precision, recall, f1 score) after pruning (to solve the problem of overfitting) is ranging between 60 to 70%. Random Forest classification accuracy is 65 to 70%. Whereas KNN classification accuracy is only 40% without normalization. But with normalization it is 60%.
- Feature importance for random forest is given below. It is used to determine which feature helps best at distinguishing a class from other present classes.

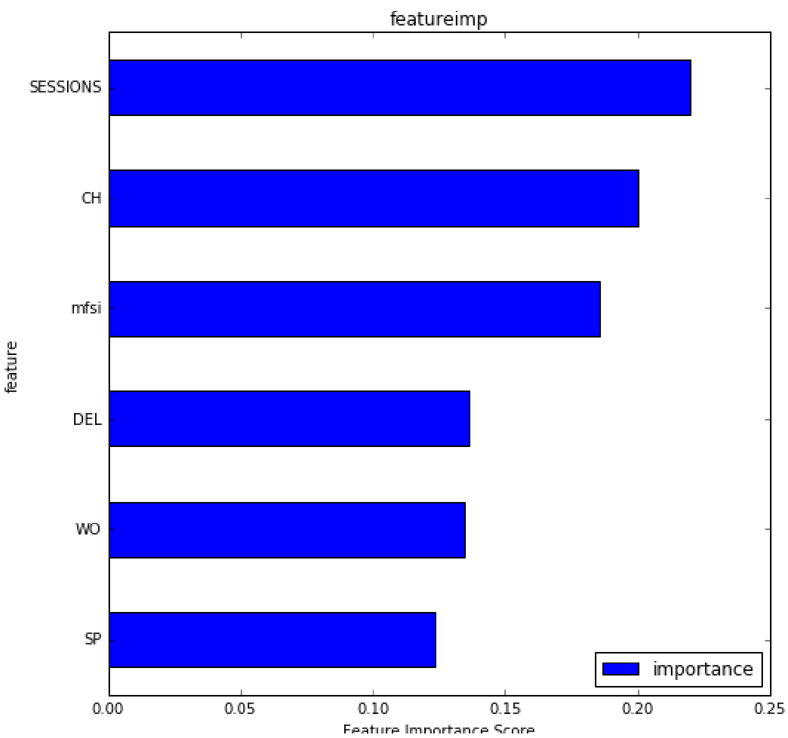



Figure 3.1 Feature importance for user 1

## Visualization of decision tree:

Class 1: Happy/Normal   Class 2: Sad/Sleepy   Class 3: Excited/ Surprised Class 4: Stressed

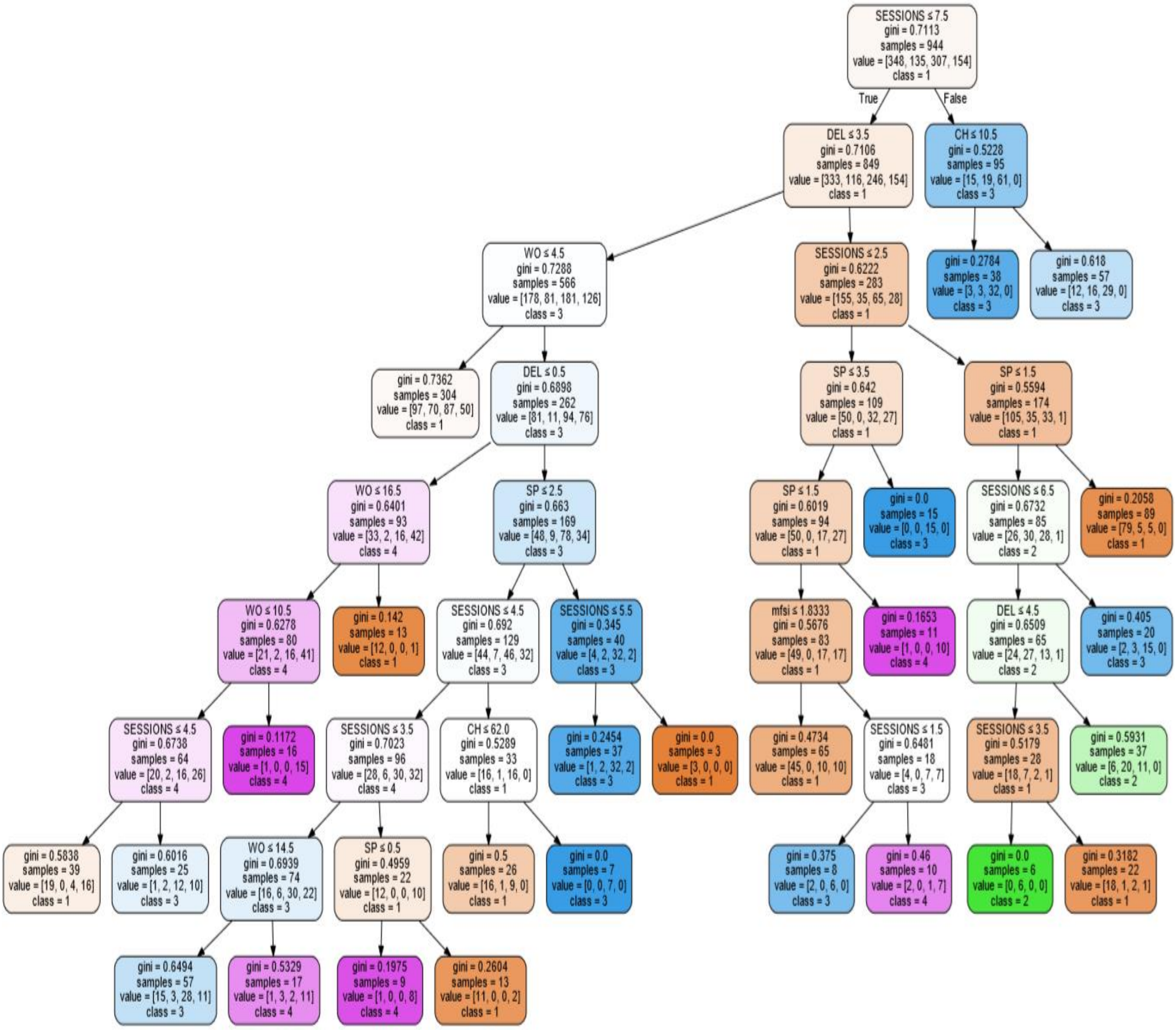



Figure 3.2 Decision tree visualization for user 1

- Using python libraries Graphviz and PydotPlus Visualization is generated.
- Here criterion used is Gini index.

**Mean value error for emotion prediction for different values of K (from 3 to 20) in KNN, K=3 gives best:**

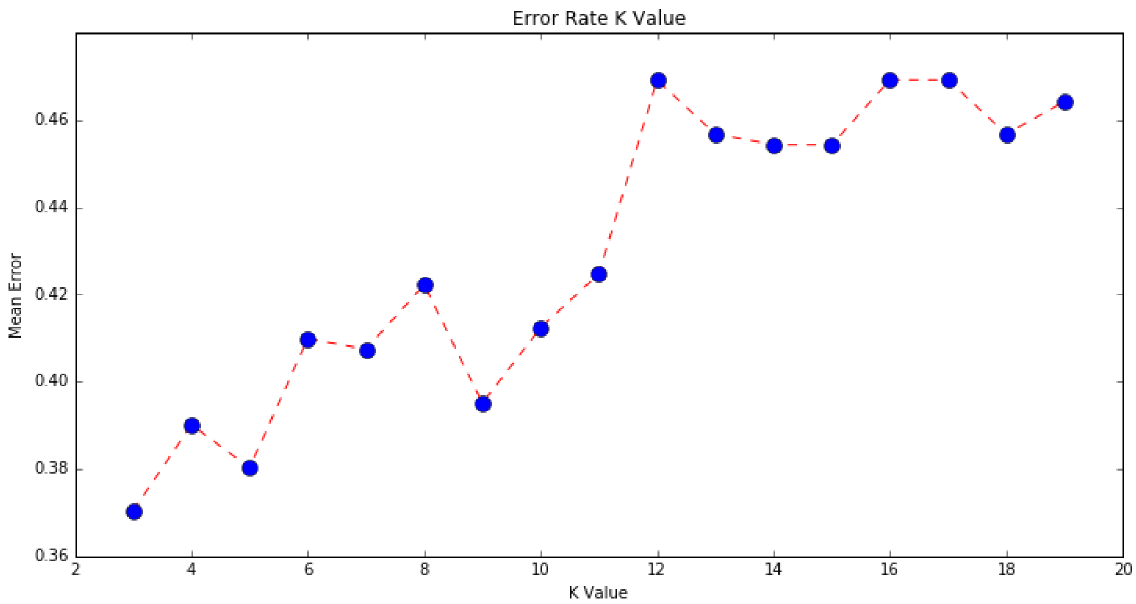



Figure 3.3 Mean value error of KNN for emotion prediction for user 1

## User 2:

- Second user's typing data of 1 week (4000 typing records) is collected along with heart rate and self-reported emotion state. After feature extraction 70% data is used for training and 30% data is used for testing.
- Decision tree and random forest classification accuracy for second user is 90 to 95%. Whereas K-Nearest Neighbor classification accuracy with normalization is 98% and without normalization it is 85%.
- Without heartrate it is 76%.
- Feature importance for random forest is given below.

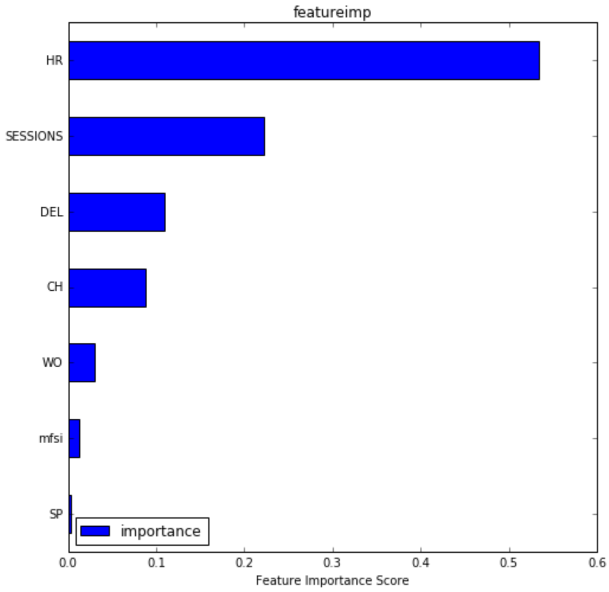



Figure 3.4 Feature importance for user 2

## Visualization of decision tree for user 2:

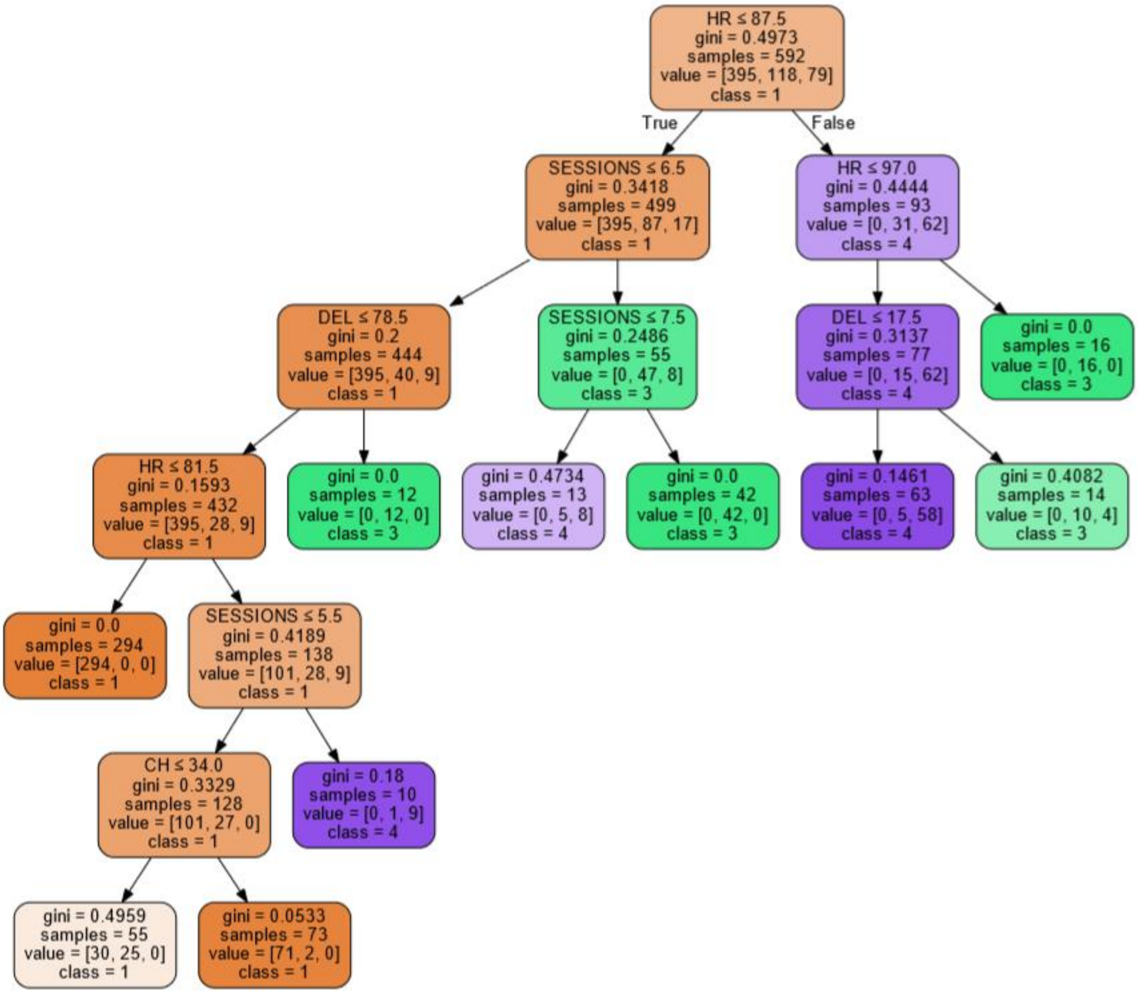



Figure 3.5 Decision tree visualization for user 2

### Mean value error for different values of K, K=3 gives best:

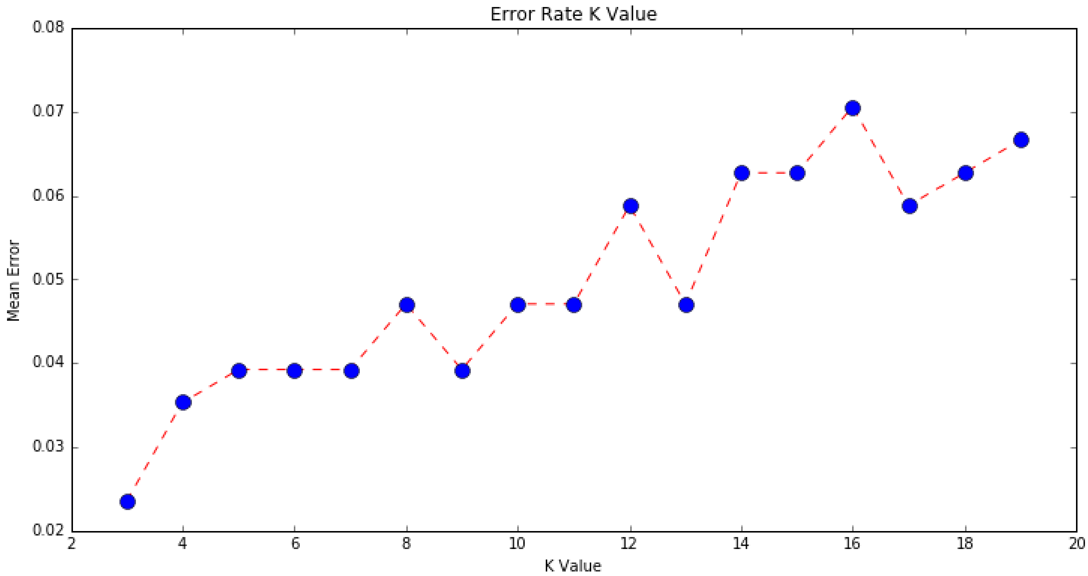



Figure 3.6 Mean value error in KNN for emotion prediction for user 2

### User 3:

- Third user's typing data of 1 week (2273 typing records) is collected along with heart rate and self-reported emotion state. After feature extraction ,70% data is used for training and 30% data is used for testing.
- Decision tree and random forest classification accuracy (precision, recall, f1 score) for third user is 80 to 85% for typing data along with heartrate. And for typing data without heartrate it is 71%. Whereas K-Nearest Neighbor(K=5) classification accuracy is 85% with heartrate and 62%without heartrate.
- Feature importance for random forest is given below. It is used to determine which feature helps best at distinguishing a class from other present classes.

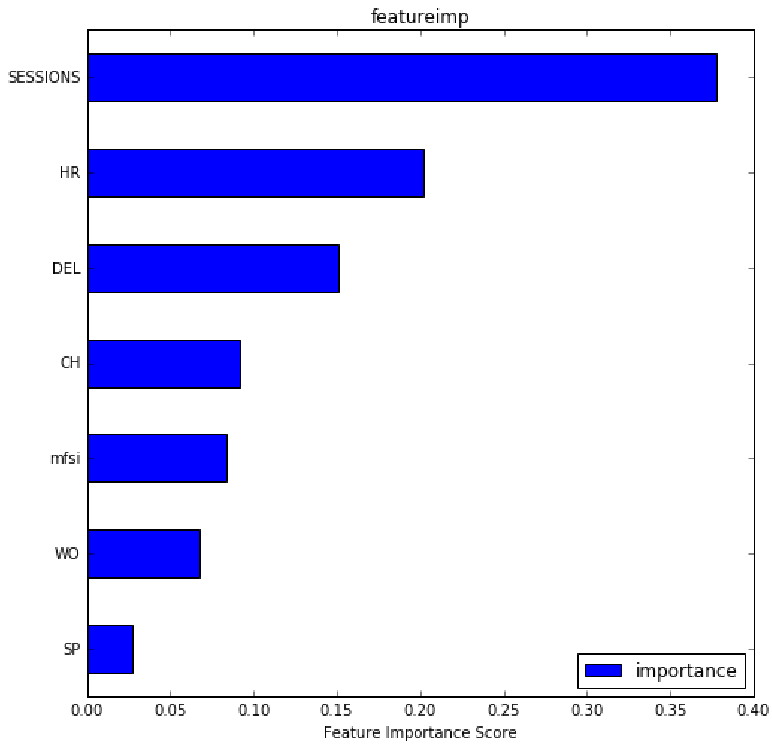


Figure 3.7 Feature importance for user 3

## Mean value error for different values of K, K=5 gives best:

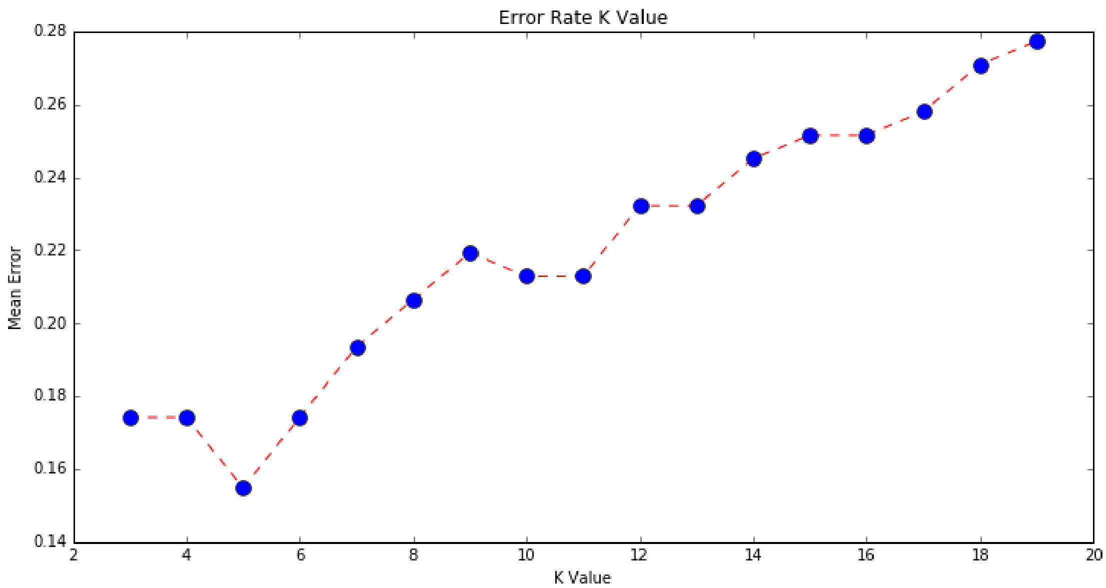


Figure 3.8 Mean value error for emotion prediction for user 3

## Visualization of decision tree for user 3:

Class 1: happy, Class 2: sleepy, Class 4: stressed

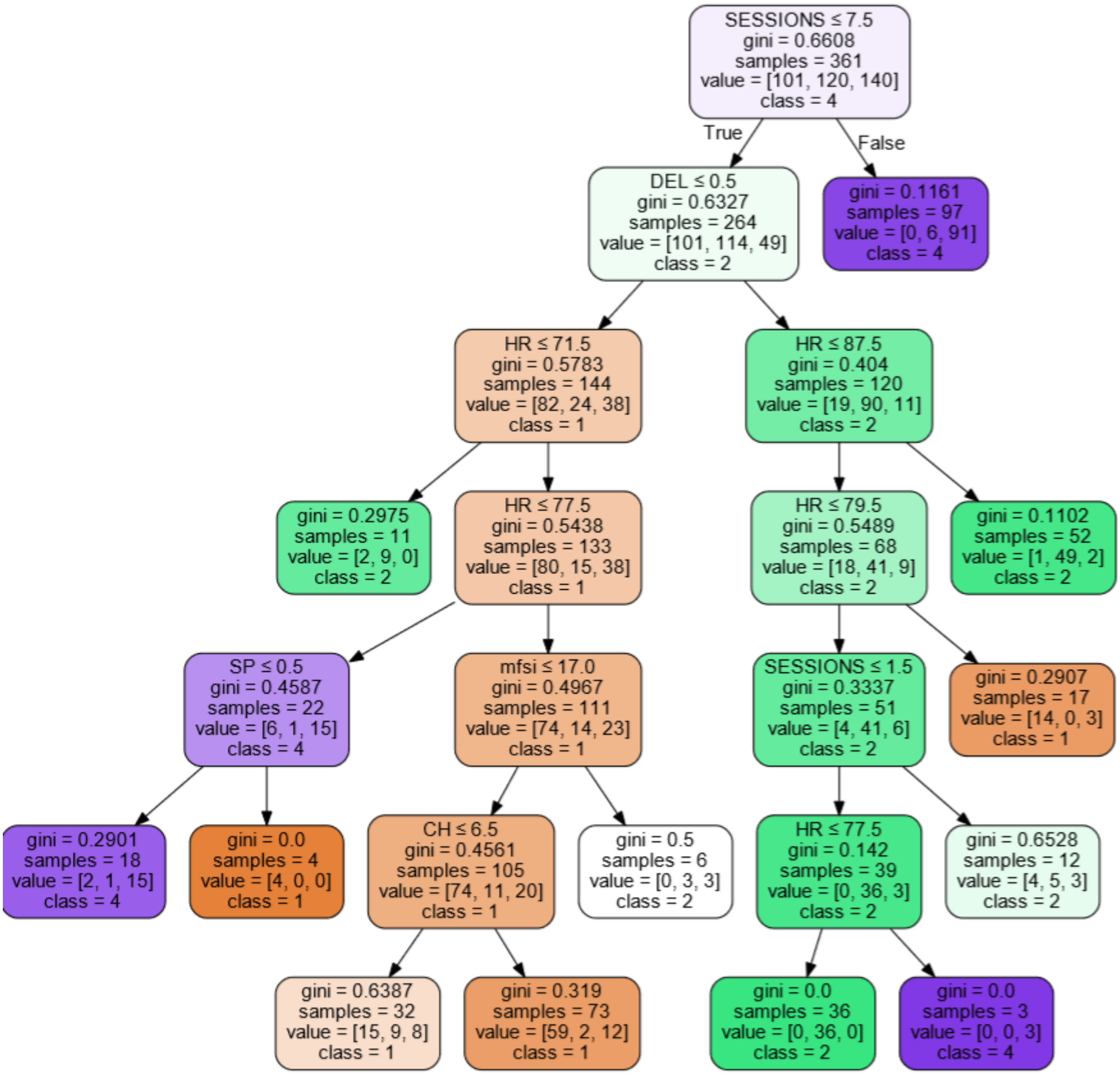



Figure 3.9 Decision tree visualization for user 3

# Chapter 4

# Discussion and Conclusion

- An important question that this work addresses is how strongly is smartphone typing correlated to our perceived emotion.
- From the experiment on three different users, it can be seen that emotion classification accuracy from typing pattern data varies from person to person. So, we can say that for some people emotional influence on typing pattern is high and for some it is low.
- Here, the dataset is imbalanced dataset containing the different emotion classes. So, for checking the accuracy of the classifier precision, recall, f1 score are taken into the consideration.
- For KNN emotion classification accuracy is high after normalization compared to before normalization.
- Using heart rate with typing data improves the accuracy of prediction model than without heartrate. So, we can say that while typing, heartrate variability is dependent on emotional influence.
- From all three experiments the analysis reveals that among different features, number of sessions is the most discriminative one and number of special characters typed is the least important one.
- The limitation is if emotion state of one user varies during a single (typing) conversation, it becomes difficult to capture that.

# Future Scope

- In the future along with typing data application name can be taken as an input. So that we can see that is there any emotional influence on application usage along with typing data? (for e.g. if a person is excited then number of times in a day, he/she is using WhatsApp is increased or not?)
- Also, we can check that does the heart rate change with the application we use? Does it impact the emotion?
- One more feature can be extracted that is number of pauses in a session.
- For example, if inter tap distance between two consecutive keypress events is greater than 15 seconds then it should be considered as pause.
- On a large scale, after finding users with similar typing characteristics aggregate model can be used for testing rather than personalized model.
- For e.g. when user 2 is stressed at that time number of typing sessions are less compared to user 3. So, both the user's typing characteristic is not similar. So, we should not use aggregate model for these 2 users.

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