# EmotionSensing: Predicting Mobile User Emotions

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***Abstract*— User emotions are important contextual features in building context-aware pervasive applications. In this paper, we explore the question of whether it is possible to predict user emotions from their smartphone activities. To get the ground truth data, we have built an Android app that collects user emotions along with a number of features including their current location, activity they are engaged in, and smartphones apps they are currently running. We deployed this app for over a period of three months and collected a large amount of useful user data. We describe the details of this data in terms of statistics and user behaviors, provide a detailed analysis in terms of correlations between user emotions and other features, and finally build classifiers to predict user emotions. Performance of these classifiers is quite promising with high accuracy. We describe the details of these classifiers along with the results.**

## I. Introduction

Pervasive context aware services provided via mobile devices such as smartphones to the users are increasingly becoming common these days. These services rely on factors such as current location, mobility pattern and activity of the users as well as the environmental factors. A very important factor that can result in providing better, customized service to the users is their emotions. For example, a music recommendation service could recommend an appropriate music to a user based on his/her current emotion. Furthermore, emotions of users have a strong impact on their behavior, actions as well as their interactions with other people, and indeed these have been studied for a long time [1]-[3].

Traditional methods of detecting user mood and emotions rely on physiological sensing (heart rate, blood pressure, body temperature, breathing rate, etc.) and body sensing (facial expressions, voice and speech, body movements, etc.). However, these methods are impractical for building emotion-based context aware applications as they are intrusive and require users to equip with instruments that they do not carry normally. With near ubiquitous pervasiveness of smartphones, a natural question arises, whether it is possible to detect user emotions based on their smartphone activities. In particular, are there any differentiating attributes exhibited by people with positive or negative emotions in their smartphone usage? If so, can we build accurate classifiers that can predict user emotions from their smartphone activities over time?

To answer these questions, we have developed an Android application called EmotionSensing to collect relevant user data to provide us the ground truth. The application runs in the background on users' smartphones and collects two sets of information about the users. The first set of information includes users' current emotions, place they are at, and the activity they are currently involved in. This information is entered by the users at regular intervals, e.g. every four hours. The second set of information includes current time and day, latitude and longitude, and a list of currently running foreground and background apps. This information is collected automatically in background every one hour. EmotionSensing transfers all the collected data to our server on the cloud, whenever the smartphone is connected to a power source. We recruited 20 users to use EmotionSensing for a period of three months, and this has provided us with a very rich and valuable dataset that is analyzed in this paper. Deployment of EmotionSensing app and the collection of this data has been approved by the authors' Institutional Review Board. In addition, we conducted an initial pilot group study and a post field group study, each lasting one week, to first inform the design of EmotionSensing and then later to assess the utility of EmotionSensing. In this paper, we describe the design of EmotionSensing, details of the data collected from the field study, and the results of the pilot and focus group studies. We describe the user behavior gleaned from the data collected, and then study correlations between user emotions and features such as user activities, places, time-of-day, gender, etc. Finally, we build classifiers based on these correlations to detect user emotions from those features. This paper makes the following important contributions:

1) Users often have mixed emotions that cannot be fully described by a single emotion in an emotion list. Indeed, users are often conflicted about whether their current emotion is happy or relaxed for example. We address this issue by allowing users to select up to two different emotions in our app. We believe that this is the first paper that addresses this important issue of mixed emotions.

2) We provide a detailed analysis of how users' smartphone activities are related to their emotions, and demonstrate the feasibility of predicting current emotions of the users from their smartphone activities with high accuracy.

3) We have collected a rich user data that provides great insights and ground truth into user behaviors as related to their emotions. We intend to release this dataset to the research community for further research in the future.

## II. Related work

Researchers have recently started looking at the problem of predicting user behavior analysis and monitoring their mental health from their social network and smartphone activities [4]-[5]. In [6]-[7], the authors have investigated Twitter to understand the nature of positivity and negativity attributes of the users. In [8], it is shown that mobile phones can be used to


http://dx.doi.org/10.1145/3110025.3110127

monitor individuals affected by depressive mood disorders by analyzing only their mobility patterns from GPS traces. In [9], the correlation among stress, sleep, activity, mood, sociability, mental well-being and academic performance of a single class of 48 students across a 10-week term has been studied. This study shows how mental health and educational outcomes of the student body have been affected from the automatic objective sensor data from smartphones. In [10], a persuasive personal monitoring system for bipolar patients has been developed. In [11], a Bayesian Network classifier is used to recognize emotional states of a smartphone user without any additional sensors by analyzing tweets that a user sends. An accuracy of 67.52% is achieved using Bayesian Network classifier to classify user emotions into happiness, surprise, anger, disgust, sadness, fear and neutral [12]. Finally, in [13], a location-based mobile social app is designed that logs and shares user emotions in a spatiotemporal and privacy preserving manner.

## III. EmotionSensing App Design

EmotionSensing app is comprised of four screen. The first (home) screen is comprised of four buttons, Emotion, Location, Activity and Done. The Done button is active only after the user has completed entering the emotion, location and activity information. The emotion, location or activity screens appear when the user taps the Emotion, Location or Activity buttons. (See Fig. 1). For emotions, the user may choose one or two options from a list comprised of “Surprised/Amused, Happy, Sad, Loved, Disgusting, Excited, Relaxed, Angry, Fearful, Confused, Stressed, Excited/Tired, Bored”.

A user may choose two emotions simultaneously at a time, which is an important differentiating feature of this project. This feature of choosing up to two different emotions addresses a common scenario where users often have mixed emotions. We will see later that this feature allows users to express their feelings in a better way and in turn significantly helps in improving the performance of the prediction model. For location, the user may choose one option from a list comprised of “Work, Home, School, Grocery store/Mall, Restaurant, Coffee Shop, Gym, Outdoor activities, Party/club, Religious places, Other places”. For activity, the user may choose one option from a list comprised of “Working, Eating/Drinking, Studying, Sports/Exercise, Cooking, Shopping, Socializing, Watching movies/TV, Social media activities, Musical activities, Reading, In-between activities, Religious activities, Other activities”.

In [12], it was observed that it is important to collect user emotion data quite frequently, more often than four hours a day. Accordingly, we provided an option to our users to report their data every 2, 3 or 4 hours. In addition, every hour EmotionSensing automatically collects user’s location (latitude and longitude), apps that the user is running, time-of-day and day-of-week. The reason for collecting location information here, even though the user manually enters the place he or she is currently at is that after the user has used the app for some time, EmotionSensing can automatically detect whether the user is at home or work, etc. The user will no longer have to manually enter a place after this time.

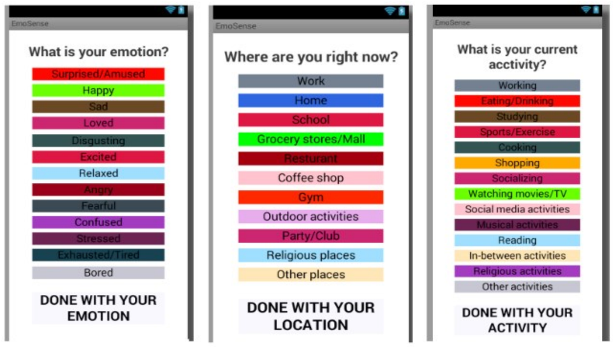


Fig. 1. A screenshot of an EmotionSensing application on our mobile client

## IV. Data Collection and Statistics

We recruited users for our field study by sending emails using the email lists to the Engineering, Psychology and Linguistic departments at our university. To encourage users to use our app, we offered a $100 gift certificate to the first twenty users who downloaded and used our app for at least two months. We required users who installed our app to report their emotions, locations and activities at least four times per day for receiving their gift card. Out of the 20 users, we had one saleswoman, one software engineer and the rest were college and graduate students in different majors - 7 in Computer Science, 2 in Cognitive Science, 6 in Linguistics and 4 in Psychology. They aged between 20 and 34 years with equal number in both genders. User had the choice to terminate the use of the application any time and uninstall the application. Overall, 27 users used our app at various times with 20 users using it for at least two months.

We collected data from April 2015 to July 2015. It contains four tables (background data, emotions, locations and activities) with 27 users, 43,116 background data, 6,123 emotions, 6,139 locations, and 6,152 activities. Of these, we selected 20 users who had used the app most. The cleaned dataset contains 40,747 background data, 6,009 emotions, 6,030 locations, and 6,035 activities. In continue, we will study and discuss about the characteristics of EmotionSensing entries that will be applied later as our classifier features.

### A. *Daily Entries Response Rate*

In the cleaned dataset, we have three users with average 2 entries per day, two users with average 3 entries and 15 users with more than 4 entries per day. Thus 75% of our users used the app four times or more per day. Furthermore, 50% of our users used our app five time or more per day. From the temporal usage of our app, we see the highest number of entries between noon and evening time intervals. Furthermore, Weekly pattern of temporal usage shows that the app usage decreases as the week progresses, except Tuesdays. This indicates how much more people are active on the second day of the week, compared to the rest of the days. These differences on different days of a week as well as over different time intervals of a day confirm previous works [7], [14] and can be useful in our emotion prediction model.

### B. Emotion Distribution

Among user emotions selected by the users, 72.5% are single emotions and 27.5% are double emotions, which means that users often preferred to select a second emotion from the list to describe their emotions. Fig. 2 shows the distribution of all emotions including single and double emotions. In this figure, each column shows the number of times a particular emotion was chosen. Some of those choices were made as part of two emotions chosen by the user. The presence of other emotions in each column indicates the number of times that emotion was chosen with other emotions. For example, we can see that Relaxed is chosen the maximum number of times followed by Exhausted/Tired and Happy. We can also see that a big portion of Happy column is filled by Relaxed, which means these emotions are often selected together by the users.

Overall, there are 91 emotion possibilities (13 single emotions and 78 double emotions). In our dataset, we observed 84 distinct values, 13 single emotions and 71 double emotions. Therefore, there are 7 double emotions that were never selected, for instance surprised/fearful, angry/loved, etc. From the 71 double emotions in our dataset 39 (54.9%) are selected less than 10 times, 21 (29.5%) are selected more than 10 times but less than 40 times, and 11 (15.5%) are selected more than 40 times. Second emotion can be used as an extra feature for predicting the users' emotions.

Fig. 3 shows the distribution of 13 single emotions and 11 most frequently-chosen double emotions. We see that some of these double emotions were selected more than single emotions. Therefore, these double emotions can be categorized as a new emotion category. For example, the double combination of Happy and Relaxed was selected more than any other single emotion except Relaxed, Exhausted/Tired, Happy and Stressed. Overall, Figs. 2 and 3 confirm that providing the option of selecting two emotions to the user is useful. In other words, users are often unable to describe their feelings via a single emotion. Since we only collected data from 20 users, which resulted in less number of entries for most of double emotions, we will use this emotion correlation between two different emotions as a new feature to train our prediction model to predict users' emotional state. We will also use this correlation matrix as voting measures in our classifier's design discussed in Section 4.

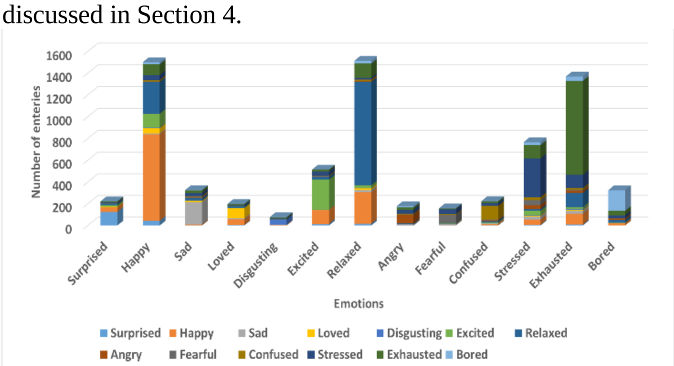


Fig. 2. Distribution of user emotion entries

### C. Running App Distribution Usage

Next, we look at the distribution of the currently running apps on users' smartphones. Recall that this information is collected every hour. In our dataset, total number of entries for apps is 280,819 resulting from 406 distinct apps. We also observed that a large number of these 406 distinct apps were used for only a small number of times and a small number of these 406 distinct apps were used for a large number of times. For example, 68 apps were used for only one time and one app was used for 17,724 times. Fig. 4 shows the top 20 apps with highest number of launch. We use the categories defined in Google Play to group these apps into 19 different categories as: Search engine/Browser, Email, Cloud, Communication, Content_text, Online shopping, Music/Audio, Media, Games, Photo, Reading, Education/Language, Transportation/Travel, Navigation, Tools, system, Notes, Utilities, Productivity. We can see that Communication with 6822 ranks as the highest usage category and Cloud with 154 ranks as the lowest usage category. We use this usage distribution in our prediction model.

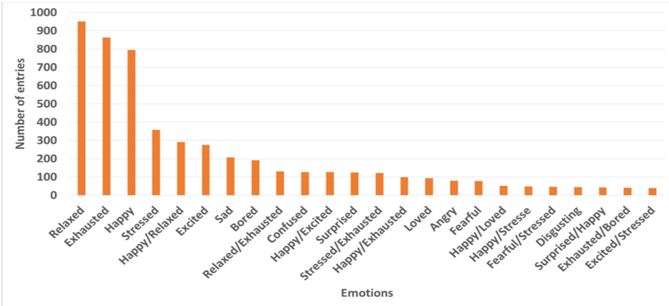


Fig. 3. Distribution of user emotion with the highest entries

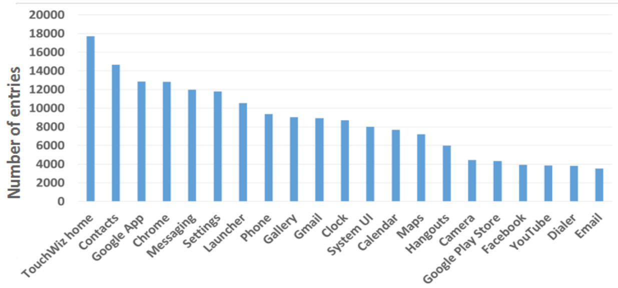


Fig. 4. The 20 apps with the highest number of usage

### D. Usage Place and Activity distribution

Fig. 5 shows the distribution of a) places and b) activities entries. From Fig. 5(a), Home is selected as the place in 56.8% of the times users used the app. In addition, since most of our users are students, School is the second highest selected place as well as Work. Activities are much more distributed (See Fig. 5(b)). Other activities with 20% and In-between activities with 14.2% of entries have covered a large percentage of selected activities, which confirms users' feedback about the limited number of activity choices.

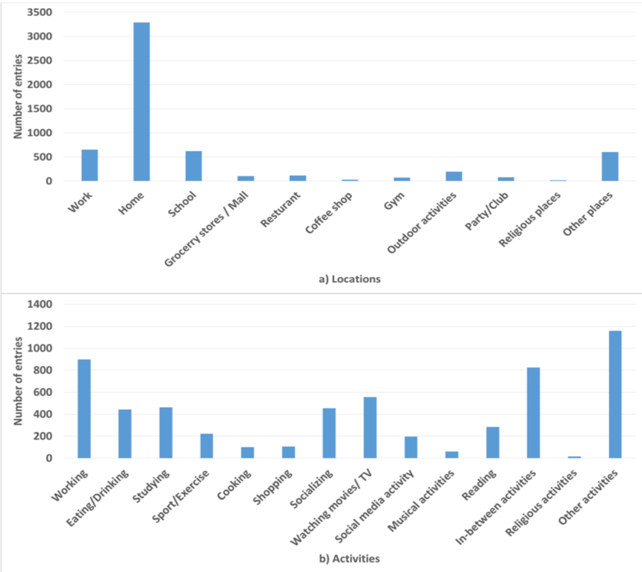


Fig. 5. Distribution of user entries a) place b) activity

### E. *Gender Behavior*

Prior research has shown that there is a high correlation between gender and the way users express their emotions [14], [15]. We observed gender differences in expressing emotions associated with time, locations, activities and running apps. We have equal number of males and females among our 20 users, which helps avoid any bias in our study and analysis. Our study shows the differences between males and females in when and how many times they used EmotionSensing.

In general, we observe that females have more emotional periodic behavior, and in addition, they are more open to sharing their negative feelings than men. For example, we can see how females are more in loved and they are more surprised compared to males. At the same time, they are also more in sad, bored, stressed and confused categories of emotions. According these observations, gender can be consider as one of the effective features in emotion prediction design.

## V. EMOTION PREDICTION

The data collected from the field study Given that there are 13 different emotions, the amount of data we have is not large enough for this 13-class classification. Therefore, we have used one versus all others as binary classifiers for classifying each emotion. We have used supervised learning method for building our classifier. To determine the best suitable classifier, we experimented with several different classification algorithms, including logistic regression, naive Bayes, Support Vector Machine and random forest. We found that the best performing classifier was random forest. Because of relatively large number of attributes in our dataset, decision tree approach results in better performance. Random forest performs implicit feature selection and provides a pretty good indicator of feature importance. In all of our analysis, we use 10-fold cross validation, with equal number of attributes, as one versus all, over five randomized experimental runs to find optimal results. The emotions' correlation matrix is calculated based on Fig. 2. At the end we presented a methodology using correlation matrix as voting measurement on top of binary classifiers to predict the users' emotional states.

### A. *Generalized Emotion Prediction Model*

#### 1) *Binary Classification*

To train our generalized classifier in the first step, we use all our collected data including all presented features with 10-fold cross validation. We have a set on one-vs-all random forest decision trees. To show how much choosing a second emotion by some users and considering it as an extra attribute in our classifier design affect our classification performance, we compare the recall and precision values of each emotion before and after considering the second emotion in Table 1.

Because the data set for most emotions is quite small, precision values in most classes are low, while we got large recall values. Since we have used binary classification, every emotion other than the emotion being classified is considered negative data. This implies that every other emotion is opposite of the emotion being classified. This is not accurate as several different emotions are positively correlated and are not necessarily opposite of each other. By having large and equal number of data for all emotions, precision values can be improved. This is evident from the results of three emotions of Happy, Relaxed and Exhausted. As these emotions have the highest number of entries in our collected data set, their classification performance including precision and recall are quite high. Disgusting has the lowest amount of data in our data set, which has resulted in the lowest value of precision. We can improve performance using emotion correlation matrix as a voting measurement as discussed in the next subsection.

Table 1 also shows how much using a second emotion as an extra attribute improves both recall and precisions for all emotions. For example, in some emotions such as Excited and Stressed, we observed around 20% precision and recall improvement. Finally, we found that both precision and recall values when second emotion is used are significantly higher (t-test, p-value <=.0001).

Another informative attribute which has to be considered in our classification result is gender. As we mentioned before our participants are equally divided into two genders. We designed two separate classifiers for two genders and compared the results with our generalized classifier for all users. According to the results, male-classifier performs better than all-classifier, (precision, recall: t-test, p-value <=0.04, <=0.02), while there is no big difference between female-classifier and all-classifier (precision, recall: t-test, p-value <=0.2, <=0.1). This would be because of consistency of males in their mood selection comparing females. Fig. 6 shows Recall values for each emotion corresponding to all users, males and females. From this figure we can observe for all emotions except Angry and Confused, male-classifier outperforms the others. Results of our generalized classifier demonstrate two important points. First, adding the option of second emotion choice in EmotionSensing is the right option, and second, gender-based classifiers can result in improving the accuracy of the classifiers.

TABLE I. BINARY CLASSIFIERS' PERFORMANCE BEFORE AND AFTER CHOOSING A SECOND EMOTION

| | **Before** | | **After** | |
|---|---|---|---|---|
| **Emotions** | *precision* | *Recall* | *Precision* | *Recall* |
| Surprised/Amused | 10% | 67% | 16% | 82% |
| Happy | 42.5% | 72% | 72.6% | 85.4% |
| Sad | 11% | 70% | 27% | 82% |
| Loved | 8% | 64% | 11% | 83% |
| Disgusting | 3% | 57% | 4% | 77% |
| Excited | 14% | 62% | 36% | 84% |
| Relaxed | 40% | 76% | 80% | 87% |
| Angry | 5% | 57% | 10% | 83% |
| Fearful | 7% | 62% | 12% | 90% |
| Confused | 5% | 60% | 14% | 77% |
| Stressed | 25% | 69% | 44% | 86% |
| Exhausted/Tired | 40% | 63.5% | 79% | 86% |
| Bored | 10% | 78% | 27% | 85% |

*2) Multiclass Classification*

As we discussed before, for emotion prediction, we used 13 binary classifiers for 13 different emotions. This would probably result in more than one predicted emotion for each record. For choosing the highest probable emotion among these, we used the emotions' correlation matrix accordingly. Emotions' correlation matrix is calculated from distribution of all emotions shown in Fig.2. This matrix shows how much each emotion is correlated with others. For example, Happy has the highest correlation with Relaxed as 19% which also can be confirmed referring Fig. 3. According to our collected data these two emotions are chosen at the same time for 291 times which is the fifth highest emotions selection (see Fig. 3).

The output record from 13 binary classifiers is a vector with 13 values including 1 and 0. For each 1, we've selected the labeled emotion and its correlation values from emotions' correlation matrix accordingly. We multiply this output into extracted vectors and then add them all to create a weight vector. If this weight vector has only one value, the corresponding emotion is the final predicted emotion, but if it has more than one value, we select the two largest weights and emotions accordingly. The reason for selecting two weights is because we let our users select at most two emotions at the same time.

Table 2 shows the precision and recall values of each emotion using this methodology. According to this table in some emotions performance has improved comparing binary classification although it outperforms binary classifiers, (precision, recall: t-test, p-value <=0.001, <=0.001). Overall accuracy using this algorithm is 75%. Compared to [12], our classifier's performance is better by almost 7.5%.

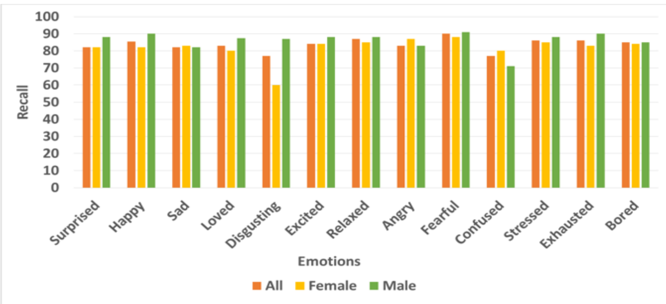


Fig. 6. Recall values across all/female/male users

TABLE II. MULTICLASS CLASSIFIER'S PERFORMANCE

| | **Multiclass** | |
|---|---|---|
| *Emotions* | *Precision* | *Recall* |
| Surprised/Amused | 33% | 65% |
| Happy | 65% | 83% |
| Sad | 35% | 76% |
| Loved | 28% | 45% |
| Disgusting | 11% | 57% |
| Excited | 54% | 68% |
| Relaxed | 81% | 86% |
| Angry | 30% | 47% |
| Fearful | 19% | 60% |
| Confused | 31% | 64% |
| Stressed | 58% | 84% |
| Exhausted/Tired | 81% | 84% |
| Bored | 39% | 70% |

## B. *Personalized Emotion Prediction Model*

Our final goal has been predicting the emotional state of each individual user based on his/her history of phone usage. This personalized classifier would act as our generalized emotion detection model. The only difference is that this classifier is based on the data collected from a single user. Therefore, it is important to note that the results of a personalized classifier are trustful only of there is sufficient amount of data available for that user, which means this classifier can be used only after a user has undergone training for a sufficiently long period of time. This leads us to develop hybrid emotion prediction model. To understand this, we first build a personalized classifier for each individual user u only based on his/her collected data. In Table 3 the performance of personalized classifier for two individual users has been presented. According to this table, user1 and 2 have different number of entries, 96, 811 respectively in our dataset. A user may not go through every one of the 13 emotions we used. So, we decided to not consider those emotions of a user that were reported less than 10 times in building our personalized classifiers. According to this table, for user 1, the only possible prediction is for three emotions, Happy, Excited and Exhausted/Tired with very high accuracy. In the other hand, User 2 has a large number of data entries containing all emotions. Therefore, predicting all emotions of this individual user is possible based on her usage.

The question here is what would be our action when we don't have enough number of data for an individual user? Or how we can predict the emotional state of a new user that has been recently downloaded this app. We proposed a Hybrid emotion prediction model to solve this problem.

This classifier is built for user u by combining the all available data from other users and 75% of the users' u data. We apply this classifier to the first 25% of u's data. Results for all users, shows hybrid model performs better than personalized model, while for some users, personalized model performs better that hybrid model, depending on the amount of user available data. Table 4 shows the hybrid classifier performance for the same users in table 3 According to this table and in comparison with table 4, for user 1 with 96 data entries, both recall and precision values in all 13 emotions have been improved, (precision, recall: t-test, p-value <=0.002, <=0.04). Although, I comparison with user 1, for user 2 with 811 data entries, we do not see any improvement in classifiers' performance, (precision, recall: t-test, p-value <=0.2, <=0.2). These observations show that the hybrid model is able to capture the common patterns across all users and incorporates them with individual user's data with no enough number of entries to improve the performance for that user.

TABLE III. PERSONALIZED CLASSIFIER PERFORMANCE FOR TWO DIFFERENT INDIVIDUALS ASSOCIATED WITH TWO DIFFERENT NUMBER OF DATA

| | **User 1** | | | **User 2** | | |
|---|---|---|---|---|---|---|
| **Emotions** | *#of Emotions* | *Precision* | *Recall* | *#of Emotions* | *Precision* | *Recall* |
| Surprised/ Amused | 0 | | | 12 | 2.8% | 73.3% |
| Happy | 27 | 51.4% | 91% | 125 | 48.8% | 81.6% |
| Sad | 3 | | | 27 | 8.7% | 86.15% |
| Loved | 1 | | | 19 | 11% | 73.3% |
| Disgusting | 5 | | | 13 | 3.3% | 73.3% |
| Excited | 16 | 29.6% | 94% | 54 | 25.14% | 80.7% |
| Relaxed | 8 | 13.3% | 90% | 156 | 59.1% | 75.4% |
| Angry | 3 | | | 30 | 10.72% | 81.3% |
| Fearful | 0 | | | 47 | 27.75% | 90.4% |
| Confused | 4 | | | 36 | 12.13% | 77.7% |
| Stressed | 6 | 4% | 40% | 158 | 59.5% | 85.6% |
| Exhausted/ Tired | 14 | 22% | 82.8% | 96 | 39.5% | 83.7% |
| Bored | 9 | 10% | 75% | 38 | 12.2% | 73.7% |

TABLE IV. HYBRID CLASSIFIER PERFORMANCE FOR TWO DIFFERENT INDIVIDUALS ASSOCIATED WITH TWO DIFFERENT NUMBER OF DATA

| | **User 1** | | | **User 2** | | |
|---|---|---|---|---|---|---|
| **Emotions** | *#of Emotions* | *Precision* | *Recall* | *#of Emotions* | *Precision* | *Recall* |
| Surprised/ Amused | 0 | | | 12 | 16.5% | 63.3% |
| Happy | 27 | 70.8% | 97% | 125 | 76.7% | 66.5% |
| Sad | 3 | | | 27 | 17.3% | 60% |
| Loved | 1 | | | 19 | 19.4% | 71.1% |
| Disgusting | 5 | | | 13 | 7.6% | 63.3% |
| Excited | 16 | 39% | 96% | 54 | 51.7% | 74.81% |
| Relaxed | 8 | 52.8% | 93.2% | 156 | 79.4% | 69.74% |
| Angry | 3 | | | 30 | 19.5% | 88% |
| Fearful | 0 | | | 47 | 35% | 87.8% |
| Confused | 4 | | | 36 | 28.5% | 64.4% |
| Stressed | 6 | 15% | 76.5% | 158 | 71.5% | 80.5% |
| Exhausted/ Tired | 14 | 55.5% | 91.2% | 96 | 83.6% | 71.6% |
| Bored | 9 | 36% | 95% | 38 | 35.6% | 49.5% |

## VI. CONCLUSION AND FUTURE WORK

In this paper, we explore the question of whether it is possible to predict users' emotions from their smartphone activities. Using a smartphone app that we built, we have collected a valuable amount of user emotion data that is analyzed in detail. Based on this analysis, we have built highly accurate classifiers to predict user emotions from smartphone activities.

There are a number of future directions we plan to pursue. First, based on the post-study focus group feedback, we plan to incorporate some new features in EmotionSensing and then conduct a larger-scale study. Next, we plan incorporate external factors such as seasonal effect, weather, holidays, critical work deadlines, economic Investigating the effect of others' emotions on each individual's mood is another interesting factor has to be studied. Therefore, we plan use emotions as contextual features to build better context-aware applications.

## REFERENCES


[1] E. Marg, 1995, "Descartes'error: Emotion, reason, and the human brain," Optometry & Vision Science, 72(11), pp. 847–848.

[2] T. Saari, K. Kallinen, M. Salminen, N. Ravaja, and K. Yanev, "A mobile system and application for facilitating emotional awareness in knowledge work teams," *In HICSS*, Jan 7-10, 2008.

[3] A. Gluhak, M. Presser, L. Zhu, S. Esfandiyari, and S. Kupschick, "Towards mood based mobile services and applications," *In Smart Sensing and Context*, 2007, pp. 159–174.

[4] K. K. Rachuri, et al., "EmotionSense: a mobile phones based adaptive platform for experimental social psychology research," *Proceedings of the12th ACM international conference on Ubiquitous computing. ACM*, 2010, pp. 281–290.

[5] H. Lu, et al., "Stresssense: Detecting stress in unconstrained acoustic environments using smartphones," *Proceedings of the 2012 ACM Conference on Ubiquitous Computing. ACM*, 2012, pp. 351–360.

[6] M. Roshanaei, S. Mishra, "Studying the attributes of users in Twitter considering their emotional states," Social Network Analysis and Mining,Springer, 2015, pp. 5-34.

[7] M. Roshanaei, S. Mishra, "Having Fun?: Activity-based Mood Prediction in Social Media. Accepted in Social Network Analysis Lecture Notes Series," 2017, pp. 1–18.

[8] N. Yang and A. Samuel. "Context-rich detection of users emotions using a smartphone,".

[9] R. Wang, et.al., "StudentLife: assessing mental health, academic performance and behavioral trends of college students using smartphones," *In Proceedings of the 2014. ACM International Joint Conference on Pervasive and Ubiquitous Computing. (UbiComp '14). ACM*, New York, NY, USA, 2014, pp. 3-14.

[10] J. E. Bardram, M. Frost, K. Szántó, and G. Marcu, "The MONARCA self-assessment system: a persuasive personal monitoring system for bipolar patients," *In Proceedings of the 2nd ACM SIGHIT International Health Informatics Symposium (IHI '12). ACM*, New York, NY, USA, 2012, pp.21-30.

[11] H. Lee, Y. S. Choi, S. Lee, and IP Park. "Towards unobtrusive emotion recognition for affective social communication," *In Consumer Communications and Networking Conference (CCNC)*, 2012, pp. 260–264.

[12] R. LiKamWa, Y. Liu, N. D. Lane, and L. Zhong, "Moodscope: building a mood sensor from smartphone usage patterns," *In Proceeding of the 11th annual international conference on Mobile systems, applications, and services*, 2013, pp. 389–402.

[13] Y. Huang, Y. Tang, Y. Tang. "Emotion Map: A Location-based Mobile Social System for Improving Emotion Awareness and Regulation," *In Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work \& Social Computing*, 2015, pp. 130-142.

[14] M. D. Choudhury, M. Gamon, S. Counts, and E. Horvitz, "Predicting depression via social media," *In ICWSM*, 2013.

[15] A. H. Fischer, and A. SR. Manstead. "The relation between gender and emotions in different cultures," *Gender and emotion: Social psychological perspectives*, 2004, 4 (1), pp. 87–94