Leveraging IoT Device Data for Emotional Health

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Abstract. Recent evolution of wearable devices is primarily focused on physical health and fitness but ignore emotional health aspects of an individual. Current health services help user define goals "Reduce weight" but do not provide interfaces for users to define goals as "Stay Happy". Lot of existing research has focused on sensing user mood classification based on device data but there is limited research that has focused to diagnose and heal depression. A conventional method of doctors detecting depression is based on Hamilton scale of depression with a set of questions and is an intrusive method to probe depression patients. IoT devices are slowly gaining popularity and huge data that is generated from these devices can be leveraged to determine user emotional health. Proposed method attempts to analyze IoT device data and calculate user depression scale and recommends relevant social communication with user social contacts (Friends, Family Members). Identifying precise social contacts and recommending actions and content to recover from early stages of depression is one of the goals of the proposed system. Method recommends relevant social contacts based on current depression score. Proposed system tries to monitor user's emotional state and more tries to act as preventive health assistant to correct emotional states in early stages and avoids user moving to advanced stages of depression.

Keywords: IoT · Healthcare · Depression · Emotional health

1 Introduction

Emotional Health is defined as 'a positive sense of wellbeing which enable an individual to be able to function in society and meet the demands of everyday life; people in good mental have the ability to recover effectively from illness, change or misfortune'. It encompasses mental health issues like depression, anxiety, bipolar disorder, addiction, and other conditions. Depression is a condition that reportedly affects 1 in 10 Americans at one point or another. Over 80 % of the people that have symptoms of clinical depression are not receiving any specific treatment for their depression. The number of patients diagnosed with depression increases by approximately 20 % per year [1]. Long time very severe depression might lead to suicidal tendencies. So it is very important to identify person's depression state in early stages. Suicide is the 12th leading cause of death in the United States [2].

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This paper presents the method to quantify the depression level based on data streams from IoT devices. As lot of devices are getting connected in IoT space users emotional data can be derived based on his interaction with smart devices. Proposed method uses user's IoT device data, message conversations, call logs, browsing history, social activity data, photos, videos etc. to calculate emotional state of a user. It then tries to map user's emotional data to Hamilton depression scale. The Hamilton Rating depression scale abbreviated as HAM-D [4] is the most widely used clinician-administered depression assessment scale. HAM-D is a multiple item questionnaire used to provide an indication of depression, and as a guide to evaluate recovery. The questionnaire is designed for adults and is used to rate the severity of their depression by probing mood, feelings of guilt, suicide ideation, insomnia, agitation or retardation, anxiety, weight loss and somatic symptoms. There are 17 items present which are used to calculate depression scale. Table 1 represents key parameters referred in questionnaire. Four other questions are not added to total score and are used to provide other clinical information. Each item on the questionnaire is scored on a 3 or 5 point scale, depending on the item, and the total score is compared to the corresponding descriptor. Assessment time is estimated at 20 min.

Data from IoT devices and smartphone can be correlated to determine HAM-D Score. New devices like Sensiotec and Affectiva provide new sources of data.

Table 1. HAM-D params

HAM-D params	Mobile data params	IoT devices data	Fitness wearable data
Depressed mood	Call logs – low voice Message Social activity – Depressed content posted Images – Depressed face	Emospark(device) detects sadness	Low sleep Low food intake Weight loss Less Active
Feelings of guilt		Cry detection	
Anxiety	Images	Emergency Alerts, IFTTT Events (Kid Not reached home, Thief at Home)	BP data (low blood pressure), Anxiety data from Affectiva
Anxiety somatic		Jawbone UP paired with Smart things/Nest Hub	Sleep data (less sleep)
Suicide	Browsing data		
Insomnia late	More browsing/social activity while still at bed		
Work and activities			Activity monitoring (Less, Average, High)
Retardation: Psychomotor	Call content/Messaging		
Agitation	Images	Sensiotec	Stress data, Heartrate data, sweating (from wearables)
Somatic symptoms (Gastrointestinal)			Food data collected from Apps
Somatic symptoms general			Exercise Activity data
Loss of weight			Accessories (OMRON etc.), Apps(S Health etc.)
Insight	Depression App usage		

Sensiotec developed a device which can calculate person's agitation [8]. Affectiva developed a wearable device which can calculate anxiety [9].

1.1 Abbreviations and Acronyms

IoT-Internet of Things
IFTTT-If This Then That
IoHT-Internet of Health things

2 IoT Health Devices and Impact of Device Data

IoT Device Data: IoHT includes implantable devices surgically implanted by physicians, such as pacemakers, which are configured and managed externally using Bluetooth or other wireless technology. It can also include external devices that are plugged into our bodies to administer medications such as insulin pumps.

IoHT includes wearable devices that can clip to our belts, be sported on an armband or embedded into our watches or eyeglasses to measure our activity or heart rates.

IoHT includes remote monitoring devices that can be installed in a patient's home to track blood pressure, weight, blood glucose levels and other important health data. This would also include consumer electronic devices such as smartphones and tablets that run specialty health apps or are integrated into health solutions.

IoHT includes the back-end systems built to power these mobile and remote monitoring health solutions, including cloud and Big Data infrastructures and our legacy infrastructure of classical health IT systems.

Current paper focusses on wireless implantable devices, wearable devices, remote monitoring devices and IoT hubs that can be connected to smart phone over short range connectivity protocols like BT/BLE/ZigBee/Ant+. Recent evolution of home automation hubs like Nest Thermostat and SmartThings hub play important role for realizing health use cases.

Devices like Kiband, Child Angel alert parents when kids are outside proximity ranges of some meters. Also IoT Health devices like "Mimo" send parents real-time information on their baby's breathing, skin temperature, sleeping position, and activity level. Similarly IFTTT kind of automation platforms help user defines recipes (When thief at home alerts me where ever I am). Motion, smoke Detector, Door/window Sensor, Glass Break Sensor and Indoor/Outdoor Camera provide important sources of IoT data that can impact an individual emotional level. In emerging countries like India gas leak detection is a major safety concern.

Also lot of effort is going on in the development of new medical IoT devices. UroSense™ urine management system provides real-time awareness to caregivers enabling them to mitigate health and safety issues associated with catheterized patients while realizing substantial cost savings. UroSense™ provides fill level and core body temperature (CBT) data directly to a monitor or nursing station wirelessly. Also devices like Philips medical dispenser which help seniors manage on time medications when tied with other devices can generate meaningful IoT notifications to other devices. For example missed medication alerts can be sent to family member devices (Table 2).

Table 2. Different IoT device data

IOT Devices	Data inputs for emotional Health
Mimo	Temperature, sleep, breathing
Milk nanny	Milk consumption data
Listnr	Baby's cry detection
Sproutling	Heartrate, Temperature
Temp Traq	Temperature
Owlet baby care	Oxygen level, heart rate
Sensible baby	Movement, temperature, breathing
Withings home	Analyzes local sound for signs of distress
Pacif-i	Temperature, Boundary check for kid
Emospark	Emotion text and content analysis
EAR-IT	Acoustic event detection

A lot of such IoT devices and wearables help user to define automation rules like "If event X occurs trigger action A". Though these event action platforms are primarily meant to trigger critical alerts and can help them manage their day to day activities easily, they can also act as key inputs that cause anxiety which is one of emotional health parameters. Careful analysis of above data can help to measure events that can make user anxious and repeated occurrence of such events can lead to mild and severe depression.

2.1 IoT Data Processing

As explained in Fig. 3 IoT Event Action Map consists of set of IoT events coupled with space and time context. IoT Events are "Kid Missing" and "Sudden hike in BP Level of father" generated from IoT devices (Ex: kiband) and Wearable BP Monitor. Corresponding IoT Actions in such context could be to trigger real time interface to "call user X" or "Notify user Y".

Figure 1 represents flow of events. IoT Event Analyzer disseminates appropriate events and sends it to "Event to Alert Mapper" module. Alert Mapper module maps events to critical Alerts. These Alerts are then correlated using correlation engine which classifies alerts based on emotional parameters associated with the alert data and generates set of IoT Actions.

Figure 2 represents architecture of emotional health assistant platform. Various IoT Streams of data are locally analyzed to build an emotional profile. Depression or Emotion Monitor consists of IoT Event Analyzer, Event to Alert Mapper, Correlation Engine Modules se.

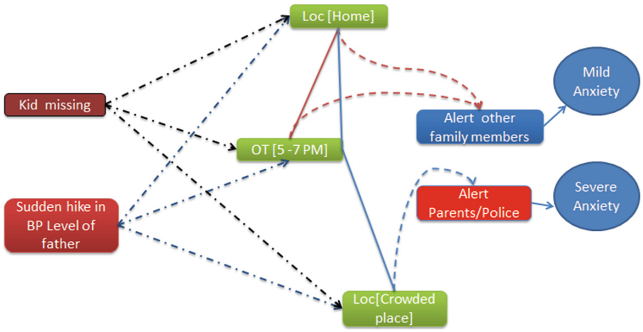

Fig. 1. IoT event action map

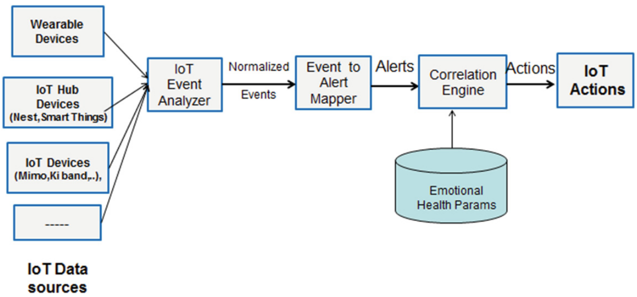

Fig. 2. IoT event data processing

2.2 Calculating Depression Score with Device Data

There are numerous IoT devices and each of these devices will generate many events. System shall determine critical events and assigns weightage and validity for each of the events. Validity here means duration till the event for which an IoT action is valid. Table 3 shows top 8 events sorted in the order of weightage.

Table 3. Weightage and validity for events

IOT Devices	Events	weightage	Validity in hrs
D1	E1	w_e^1	V1
D1	E2	w_e^2	V2
D2	E3	w_e^3	V3
D3	E4	w_e^4	V4
D4	E5	w_e^5	V5
D4	E6	w_e^6	V6
D4	E7	w_e^7	V7
D5	E8	w_e^8	V8

A list of association is maintained between a person and his set of emotional contacts. Table 4 shows user top six emotional contacts along the weightage. Weight represents the emotional connect between that person and user.

Table 4. Weightage and persons

Contacts	Weightage
P1	w_p^1
P2	w_p^2
P3	w_p^3
P4	w_p^4
P5	w_p^5
P6	w_p^6

When events are triggered from IoT devices, system will know person to event association. To find the criticality of the event, system will take sum of wex and wpx. [Table 5] shows 5 sample events sorted based on criticality. For ex: P1-D1-E1-T1 means device D1 generated event E1 for the person P1 at time T1.

Table 5. Event order and its weight

Event order	Score(S)
P1-D1-E1-T1	$w_p^1 + w_e^1$
P3-D2-E2-T2	$w_p^3 + w_e^2$
P2-D4-E5-T3	$w_p^2 + w_e^5$
P4-D5-E8-T4	$w_p^4 + w_e^8$
P6-D5-E10-T4	$w_p^6 + w_e^{10}$

Table 6. Score calculation for device data

Call variance	Message variance	Social activity variance	Image variance	DMS value
Val >=70	val <=100	val <=100	val <=20	0
val >=52	val <=200	val <=200	val <=40	1
val >=34	val <=300	val <=300	val <=60	2
val >=17	val <=400	val <=400	val <=80	3

If two events are generated at same time as shown in above table at time T4, then wp4, we8, wp6 and we10 are added to the total weight. The system will maintain the event, its generated time and validity in our system. When time elapsed more than the validity, the event will be removed.

In Fig. 3, at 1:00 h event E1 occurred having validity 5 h and at 3:00 h event E2 occurred with validity 8 h. This time validity of E1 is reduced by 2 h. More than one event can occur at same time as shown above at 12:00. At any point of time weightage is calculated as sum of weights of all the events exists in the system.

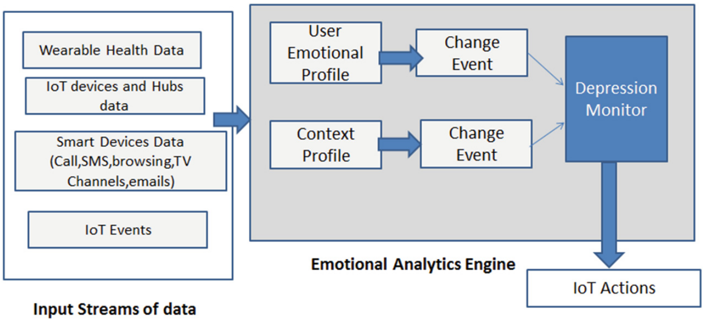

Fig. 3. Emotional health architecture

Score from the weights is calculated as below:

Events and persons are divided into 4 groups each and sum of weights for all the combinations of events and persons in each group are calculated. If present weight falls under first group then user's score for IoT device data is 4, else if present weight falls under second group then user's score for IoT device data is 3 and so on.

Call logs: From the whole call log data only favourite social contact log data is segregated. Further Variance in favourite call log data is analyzed for any change in call log durations. Variance is now associated with identifying "Depressed mood" parameter. This parameter ranges from 0–4 scale. Following formula will be used to get "Depressed mood" scale (DMS).

Call Variation = Average favorite call duration for previous 180 days/Average call duration for last week * 100.

Messages: The research paper "Social Networks" Text Mining for Sentiment Classification: The case of Facebook' statuses updates in the "Arabic Spring" Era" [4] mines the messages and tells the sentiment of that message. This system will use same method for text mining. This research is divided into 5 steps: raw data collection, lexicon development, data preprocessing, feature extraction and sentiment classification. Lexicon development phase parses the messages and finds out emoticons like "☺,:P,☹, : > , …", Interjections like "wow, oh dear, Thank you…" and Acronyms like "LOL, GR8…". To evaluate the performance of sentiment classification, they used following formulas: The accuracy (1), the precision (2), the recall (3) and the F-measure (4).

$$Accuracy = \frac{(a+d)}{(a+b+c+d)} \tag{1}$$

$$Precision = \frac{a}{(a+d)} \tag{2}$$

$$Recall = \frac{a}{(a+c)} \tag{3}$$

$$F - measure = \frac{(2 * Precision * Recall)}{(Precision + Recall)} \tag{4}$$

Where:

- a: the number of statuses correctly assigned to this class.
- b: the number of statuses incorrectly assigned to this class.
- c: the number of statuses incorrectly rejected to this class.
- d: the number of statuses correctly rejected to this class.

Negative content depresses the user while positive content makes him happy. DMS for message content can be calculated with below formula.

Message Variation Last Week = No. of negative messages in last week/Total no. of messages in last week. MessageVariationLast6Months = No. of negative messages in last 6 months/Total no. of messages in last 6 months.

Message Variation = MessageVariationLastWeek/MessageVariationLast6Months * 100.

Social activity: Similar to messages, system can find out whether social media content user posted or received is negative or positive. DMS for social media activity can be calculated with below formula.

SocialVariationLastWeek = No. of negative messages in last week/Total no. of messages in last week.

SocialVariationLast6Months = No. of negative messages in last 6 months/Total no. of messages in last 6 months.

SocialVariation = SocialVariationLastWeek/SocialVariationLast6Months * 100.

Images: There are many face detection algorithms which tells whether a person is feeling happy, sad, exited etc. For example Face.com – a face detection and recognition service will analyze the images and tells whether person is Happy, Sad, Surprised, Angry and Neutral. These services will be used for finding the emotional score of a user. DMS for image content can be calculated with below formula.

ImageVariation = No. of sad images/Total no. of images * 100. So DMS for mobile data will be (DMSforCall + DMSforMessages + DMSforSocialActivity + DMSforImages)/4.

Similarly, the score can be calculated for all the remaining 16 params in HAM-D and adding all the values will give us user's emotional score.

Apart from above mobile data, physical health data like sleep, Heartrate, Calorie intake, Calorie burnt, Blood glucose, Blood pressure, Stress will help in finding emotional score of the user.

2.3 Test Setup

Test bed shall consist of android phone running Android version 4.3 with an application build on android platform. Android phone is assumed to have aggregated data from all IoT devices and wearable devices. System is trained with 6 months of simulated data as in schema listed in Table 7. Table 8 represents actual simulated data used for building prototype. Figures 4 and 5 shows an individual data with severe depression. Score is calculated as explained in detail in Table 6. As shown in graph IoT data plays a key role in evaluation of depression data.

Table 7. Simulated data structure

Tables	Columns
Critical IoT alerts	Event: Event details Device: Device name from which event is generated Person: Name of the person this event is related to Validity: Validity of the event Time: Time when event is occurred Weight: Weightage given to the event
Contacts	Number: Number of contact Name: Contact name Favorite: Favorite or not
Call logs	Number: Number of the caller Name: Name of the caller Date: Date and time of the call Type: Incoming or outgoing Call duration: Call duration in mins
Messages	Number: Number of the sender/receiver Name: Name of the sender/receiver Subject: Message subject Content: Message content Date: Date and time of the message Type: Incoming or outgoing State: Whether message sentiment is +ve or -ve
Social activity	ID: Number of the sender/receiver Name: Name of the sender/receiver Subject: Message subject Content: Message content Date: Date and time of the message Type: Incoming or outgoing State: Whether message sentiment is +ve or -ve
Images	Path: Image path in mobile CreateTime: Image creation time UpdateTime: Image updation time Tags: Names of the persons present in image State: Whether user is happy or sad

3 Evaluations

Emotional score can vary from 0–53 based on Hamilton scale of depression. Based on this score, system can tell whether person is mildly depressed or moderately depressed or severely depressed or very severely depressed. System updates emotional score when user experiences any aggressive behaviour during call, when his face has

Table 8. Simulated data

Device data	Last 6 months avg.	Last week avg.
Call duration in mins	118.87	50.53
Positive message count	8.75	2.8
Negative message count	1.8	3.64
Positive social media count	67.74	20.8
Negative social media count	17.2	35.6
Calorie intake in kcal	1923	1042
Calorie burnt in kcal	458	156
Sleep duration in hrs.	8.25	4.1
Weight in kgs.	72	66
Heart rate in bpm	74	88
Stress level from 1–10	3	7
Blood glucose before meals in mmol	5.1	5.1
Blood glucose after meals in mmol	7.2	7.2
Blood pressure in mmHg	130/90	145/98
Depression app usage duration in mins	0	30

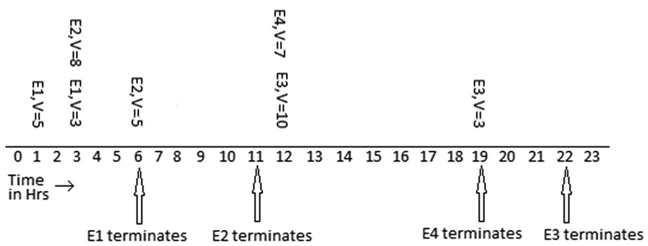

Fig. 4. Timeline for simulated events

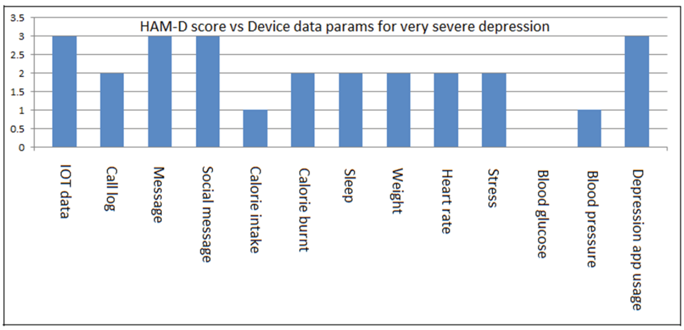

Fig. 5. Score for device data

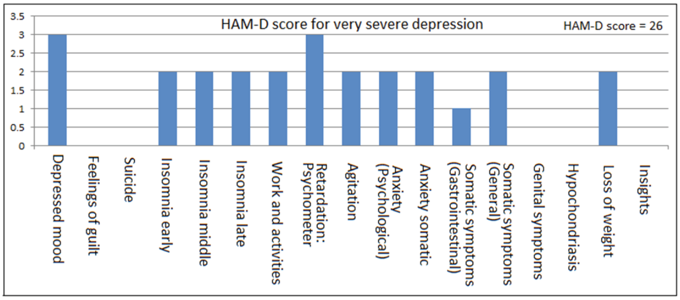

Fig. 6. Score for HAM-D params

depression feelings in the pictures taken, when he receives negative content through messages, when he posts depressed content in social media, when he searches negative content in internet. Similarly system improves emotional score when user experiences long smooth calls, when his face tells good feelings in the pictures taken, when he receives positive content through messages, when he posts happy content in social media, when he searches positive content in internet.

As per NIMH guidelines one can recover from depression by

"Try to be active and exercise. Go to a movie, a ballgame",

"Try to spend time with other people and confide in a trusted friend or relative. Try not to isolate yourself, and let others help you."

Based on user emotional state system recommends suitable activities to user. Like when user depression level is mild system recommends user to have good sleep and maintain proper food timings. When user is moderately depressed system recommends user to do regular exercises as this improves both physical and mental health. When user is severely depressed system recommends communication with relevant contacts as determined from his communication data. Recommended contacts could be a friend or a family member. When user is very severely depressed system will alert his friends/family about user so that they can give proper advice.

Based on user current depression score appropriate actions are recommended to the user which will help him to recover from his depression state. User interests are mined using Vector Space Model (VSM) [6]. VSM calculates term frequency (tf) and inverse document frequency (idf) for all the communication data (SMS, IoT Rules and Alerts, SNS posts) stored in document format. Query on system computes cosine similarity value for each of the document. Query contains all the combinations of favorite contacts with high relationship factor, all the games, and synonyms of enjoy, like, good, etc. Synonyms are identified by word net search [7]. After finding cosine similarity value for each of the document for all the queries, system will identify queries which have more cosine similarity value and suggest that activity to the user with that person (if person exists in that query).

Ex: Below are the messages posted by user
D1: After a long time our team played good cricket.
D2: Today's cricket was very good.
D3: Played football with Richard.

If suppose contacts with high Relationship factor is Richard, then our sample queries will be
Q1: good cricket Richard
Q2: good cricket
Q3: good football Richard Q4: good football
Let CosSin(D1, Qx) = Rx1, CosSin(D2, Qx) = Rx2 and CosSin(D3, Qx) = Rx3. [Table 9] shows Cosine similarity for all the documents for each of the query sorted based on CosSin values in descending order

In above document R22 > R33 > R43 > R12 then query strengths will q2 > q3 > q4 > q1.

Table 9. Cosine similarity values for queries

Query	CosSin value	Query	CosSin value	Query	CosSin value	Query	CosSin value
Q1	R12	Q2	R22	Q3	R33	Q4	R43
Q1	R13	Q2	R21	Q3	R32	Q4	R42
Q1	R11	Q2	R23	Q3	R31	Q4	R41

So, possible recommended IoT Actions could be "play cricket" or "play football with Richard".

Table 10 shows set of possible recommended IoT Actions based on user interest analysis.

Table 10. Recommended IoT actions

Recommended activities based on user's depression
Listening to music
Watching movie with A
Watching good TV shows
Showing good past moments from mobile images/videos
Suggesting to take a walk outside with B
Playing game X with C
Playing indoor sport Y with D
Suggesting to have good sleep
Suggesting to have good food habits
Doing meditation
Practicing yoga or exercise
Suggesting to read books
Suggesting gardening
Suggesting to take a short trip with group F
Take out the dog for 30 min with G
Using mobile apps
Speaking with friend H/family I
Suggesting to consult doctor

A, B, C… are user's friends/family who has done these activities or with whom user's social relationship is good. During severe depression, system will suggest very close person to the user to speak where in mild depression, system will suggest a person who is moderately close. This closeness factor can be calculated as below.

For Severe depression, system will suggest favorite contacts with higher relationship strength factor Table 11. Contacts could be family or friends. For Very Severe depression, along with suggesting contacts with higher relationship strength factor with their location, system will suggest doctors to consult and alert family members about user's emotional state.

Table 11. Favorite contacts with their relationship strength factor

Contacts	Relationship	Call duration	Message count	Social activity messages	Social activity score	Relationship strength factor
C1	Family	1739	142	1235	17.31	0.086
C2	Family	1423	104	1563	17.16	0.085
C3	Friend	1780	150	1823	20.85	0.104
C4	Friend	1041	62	963	11.47	0.057
C5	Friend	1081	89	853	11.23	0.056
C6	Others	222	21	163	2.25	0.011

3.1 Experiments

A survey was conducted on 663 random people with the age group of 20 to 45 to validate the claim as listed in Sect. 3. Set of questions were prepared to collect users' feedback. Questionnaire consists of finding user preferred mode of sharing emotions, happiness levels, sleep disturbances and user activities to recover from depression levels. Out of 663, 363 participants responded that they would talk to their friends or family members when they are depressed. In the survey taken, out of 663 participants 109 participants were Happy, 277 participants were Satisfactory and 277 participants were disappointed about their life.

Figure 6 shows survey results for participants who are not happy in their life and who are happy in their life. Figure 6(a), (c), (e) indicates 73 % of people who face high sleep disturbances, 58 % of people who never do exercise and 50 % of people who prefer not to share their emotions are unhappy in the life. Figure 6(b), (d), (f) indicates 57 % of people who are happy in their life have no sleep disturbances, 55 % people who are happy in the life do regular exercise and 72 % of people who are happy in the life speak with friends/family regularly. Survey results were indicative that good sleep, Regular exercise and speaking with friends/family keeps the participants happy. This data substantiates the claims made in the proposed system those recommendations actions as listed in Table 10 can create a positive effect on users negative emotional state.

HAM-D score is derived with inputs from survey data. Data associated with sleep, exercise data and communication patterns was extrapolated to determine score. Accuracy achieved was 55 %.

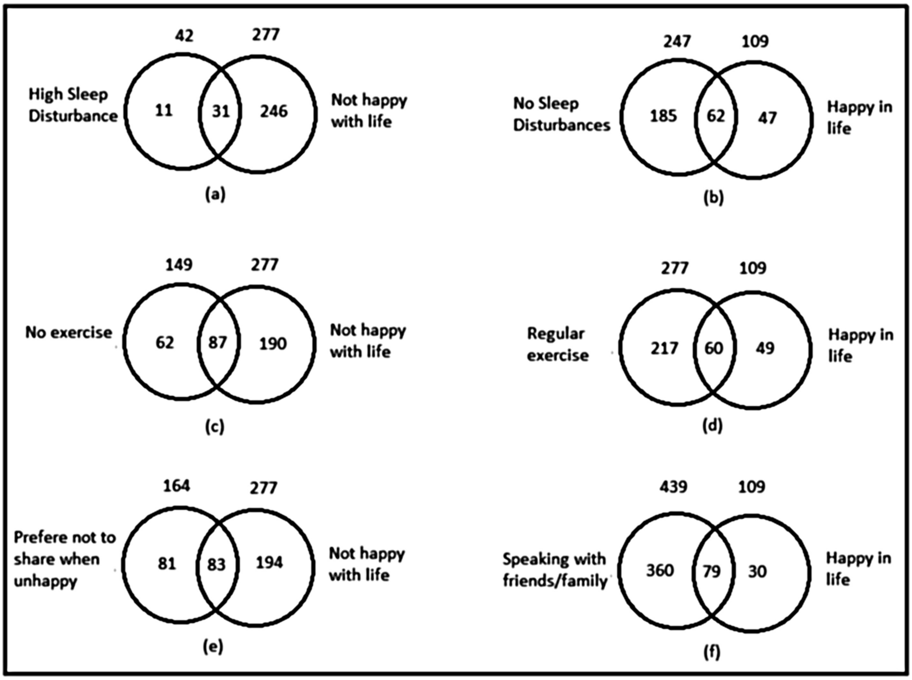

Fig. 7. Survey results

4 Conclusion

This paper analyzes the users' data from various IoT devices, evaluates the person's depression state and suggests actions then helps recover from early stages of depression. As lot of health and home automation devices get connected over IoT Networks and users' engagement on this devices increases, system can apply the above method to develop a user emotional and depression profile. Proposed method after learning about user social interactions determines the set of key emotional contacts and associated actions. We also look forward for doing further research on IoT data on cloud networks to infer more appropriate IoT Actions that can heal people suffering from mental health problems and help them lead better and happy life.

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