

# AI THERAPIST- A MENTAL HEALTH TRACKER SYSTEM

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## ABSTRACT

*In view of a mental health tracker system, a number of methods have been adopted and looked upon, including an online interactive segment, a regular record section, an analysis module, or a redirecting portal for communication and further help. With the ever-increasing data on social networking sites, sentiment and emotion analysis trackers have paved a way.*

*The purpose of this review on the mental health tracker system is to render a complete understanding of the factors affecting the mental state, getting a brief overview of the challenges associated, studying the associated aspects and thereby rendering cure with the help of analysis and evaluation.*

*Keywords: Sentiment analysis, opinion mining, psychometric analysis, mental health, therapy, depression, anxiety, web portal, artificial intelligence, state of mind*

## 1. INTRODUCTION

Mental health, which includes psychological, emotional, and social well-being, accounts for a significant portion of a person's entire personality. A person's decision-making ability, approach in making and maintaining relations, handling situations, and finding solutions is affected by their current state of mind. This emphasizes the necessity of mental wellness.

Adverse life experiences, biological factors, family trauma or a history of abuse, ongoing chronic medical ailments, chemical imbalances in the brain, use of alcohol or drugs, and even the feeling of isolation or loneliness might lead to disorder, contributing reasons for mental illness. Despite the development of mankind and augmented invested in all fronts, the sphere of mental sickness is not focused upon. Efforts to curb and handle mental state by reducing the stigma and understanding the roots, to increase the effective treatments for quality state of mind, and to identify simple factors that might help and make a change is important.

Depending upon the given situation and many necessary factors, it is important to understand that the mental health of a person can change, improve and normalize over time. It could be impacted when the demands placed on the individual exceed their coping abilities and available resources to work with, thus creating a sense of fear and depressing thoughts. Additionally, working for long continuous hours, facing economic imbalance or caring excessively might also lead to poor mental health.

Artificial Intelligence (AI) is playing an increasingly important role in mental and behavioral health treatment, as people choose ease and immediate response. Statistical data on individuals with depression who are unable to receive treatment have inspired the creation of alternate mental health care paths, many of which take advantage of technological developments with the participation of interactive chatbots, steadily rising the involvement of systems to detect, analyze and cure for a well-being. As an outcome, sentiment analysis, a psychometric analysis and a conversational pathway of opinions can be viewed as an important tool for analyzing the mood and prevalent disposition of any sample group of people about any product, service, event, or topic expressed in text form and published on social media platforms, blog posts, comments, and web reviews, among other places. Examining all posts and reviews, studying the regular patterns and frequent and integrating them into meaningful orientation may be fairly challenging from the standpoint of mining such data and opinionated text content.

The idea of a subsequent interactive mental health tracking and personality analytical system based on text analytics, to present a summary of views divided into favorable, neutral, and negative evaluations. As studied research of human opinions, viewpoints and perspectives, Opinion Mining ranks being a practical method for the analysis and expression of the human behavior. To extract and categorize attitudes from reviews, natural language processing (NLP), text analytics, and computational techniques play a vital role. The task of behavioral assessment, has a number of technical challenges involved. Right from opinion orientation- prediction and classification, object and keyword identification, psychometric categorization, expression gathering and grouping, to feature extraction, the task involves testing and learning techniques.

Particularly, due to a great rise in the amount of data available online, in the form of blogs, social networks, pictures and posts, forums; opinion mining and emotion analysis has great development prospect.

The paper aims to present an online tracking system to review, analyze and overlook the regular patterns in order to gain an insight about the state of mind, learn and apply techniques to get better with it, and work for the mental well-being of the individual. Enabling anonymity, connection, convenience with accessibility and responsiveness, privacy and access, the portal will act as a new normal to emphasize mental health as a subject of concern.

### 1.3. LITERATURE REVIEW

The development of opinion mining systems is tenuous. Working with text content identification, classification of sentiments and its orientation with distinguishing intensity levels can pose challenges. With a varied number of methods, the effectiveness of these approaches is largely determined by how well the collection of attributes used to identify attitudes is extracted.

On Twitter messages and other microblogging postings, Kouloumpis et al. emphasized the effectiveness of current lexical resources and linguistic characteristics for conduct SA. Another study using rule-based classification and supervised learning procedures revealed that hybrid classification was more relevant and yielded promising results. Since the turn of the century, SA has risen to prominence as one of the most studied areas in natural language processing (NLP). Mudinas et al. proposed a concept-level SA system (psenti), which has been demonstrated to be more successful than a lexicon-based approach. For sentiment categorization, Tripathy et al. suggested four machine learning techniques-Nave Bayes, Maximum Entropy, Stochastic Gradient Descent, and Support Vector Machine. Conducted for IMDB, their findings showed that accuracy may be attained by using progressive categorization. In their study article, A. Mitchel et al. modelled sentiment detection. Their goal was to illustrate that sentiment detection might be used to solve an issue involving sequence tagging. Their method of investigation consisted of extracting data from Twitter and converting it to text. This text was supposed to be the input dataset. Researchers looked through a sample of tweets in Spanish to perform a comparative examination of several techniques for SA and topic identification. In thorough research, lemmatizers, stemmers, n-grams, negations, valence shifters, Twitter hashtags, and semantics were investigated and presented. Socher et al. introduced a semi-supervised recursive auto-encoding technique for forecasting sentiment distributions without the need of sentiment lexica or rules that required polarity shifting, which was a unique approach.

Related works include open-domain dialogue creation and generation with large-scale language models.

Large-scale Language models: GPT (Radford et al., 2018) and BERT (Devlin et al., 2019) are typical uni-directional and bi-directional language models, respectively, that have been trained on generic text corpora, GPT-2 (Radford et al., 2019), BERT (Devlin et al., 2019), Megatron-LM (Shoeybi et al., 2019), GPT-3 (Brown et al., 2020), exceed the model scale to 1.5B parameters, exploits model parallelism and further trains 175B parameter model for autoregressive language with better NLP tasks and dialogue generation.

Open-domain Dialogue Generation: For response generation, DialoGPT is trained with GPT-2. Additionally, Meena (Adiwardana et al., 2020) utilizes social media content for training, (Roller et al., 2021) with human annotated conversations, PLATO works on discrete latent variable via curriculum learning.

## 2. METHODOLOGY

The mental health tracker portal includes:

- An interactive conversational chatbot

- Sentiment analysis through diary entry
- Psychometric analysis -personality test section
- Database integration and user profile
- Web portal divisions

This paper includes the following methodology, where based on the modules, the analysis technique is been applied. The technologies used are Django for webpage creation, PostgreSQL for extensibility and user data compliance, Naïve Bayes (set of supervised learning algorithms) for sentiment analysis and emotion mining, k means clustering (unsupervised machine learning) for psychometric analysis, and Rasa for the chatbot text generation.

### 2.1 Chatbot

Comprising of intents and entities, the chatbot works with Rasa python libraries- Rasa NLU and Rasa Core. The intents section includes the intentions derived from the text, a collection of similar phrases and responses to the specific answered to the user as a reply. Followed by Entities, these are keywords comprising of specific data, this data is further used for a discussion initiated by the user. Thereby, entities extract values and a certain pattern for the text.

Rasa NLU for Natural Language Understanding-to understand the gist of the input with intents and entities and extract specific suitable patterns and Rasa Core- to receive the first semi-processed result, further process it and deliver the final response.

Proceeding to the interpreter, extracting keywords and specific entities plays a vital role, further sent to the tracker, the other elements are hence stored inside Rasa Core. Following, the tracker keeps a note of the conversation history, the chatbot therefore, maintains the interactional state. Policy, after that, keeps a track of the action for dialogue execution, with regards the conversational history. Action here, consults the conversational state, and hence executes the final output.

### 2.2 Sentiment Analysis

Logical regression, a linear classification model, uses a logistic function to depict the probability defining the various outcomes of a single trial in this model. To simulate the statements upcoming, model evaluation- splitting into train and test data, is done. The performance of the model is measured by data training, prediction and evaluation.

By vectorizing the split, the features and patterns noted from train and test can be observed and obtained. Furthermore, in order to take into account, unknown and undefined words, to maximize learning, training and model selection is done. This ensures the working, sentiment analysis and emotion mining efficiently.

### 2.3 Web Portal Divisions

The mental health tracker system, comprising of user profile and portal homepage, login section, registration segment, diary entry page, psychometric analysis with respective tests, healing and recommendation part, and the chatbot bit takes into consideration the featured aspects for efficient emotion, personality or present state of mind prediction and delivers the output accordingly. Following this, the portal also provides a recommendation section for healing or further consultation- if any.

## 2.4 Psychometric Analysis

This section follows unsupervised learning using k-means clustering, aggregating together a collection of available data points upon definite similarities. Working with k-means algorithm, we initiated with the centroid selection, followed by iterative calculations for centroid position optimization. Cluster creation and optimization is halted when either the centroids are stabilized or the proposed number of iterations have been performed.

With the intended purpose, we worked with pandas, numpy, sklearn, scipy for k-means batch clustering and the respective computations.

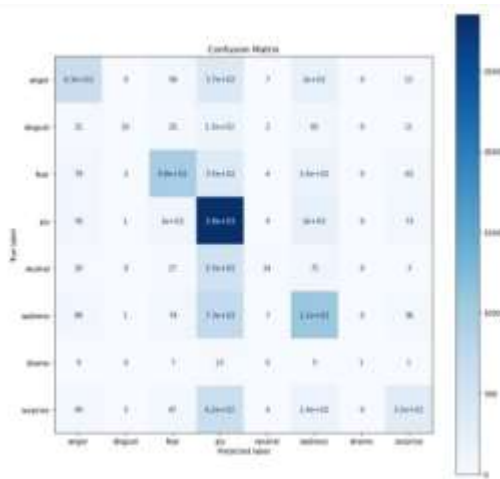
In DASS dataset for Depression check psychometric test, panda library functions have been implemented to ensure the required attributes from DASS\_data.csv file.

## 2.5 Dataset

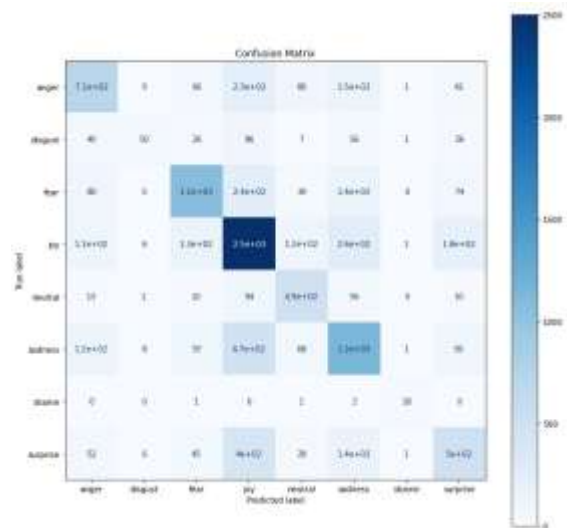
This research uses the publicly available Big Five Personality Test data from Kaggle and datasets from openpsychometrics.org- Answers to the Depression Anxiety Stress Scales. DASS\_data\_21.02.19.zip, and Answers to the IPIP Assertiveness, Social confidence, Adventurousness, and Dominance scales used as part of an experimental personality test- AS+SC+AD+DO

## 3. RESULTS AND DISCUSSIONS:

In this work, we discuss the use of AI based technologies to keep a track and improve the mental health of the user.



**Fig:** Confusion Matrix for Naïve Bayes model



**Fig:** Confusion Matrix for Logistic Regression

```
Hey
{
  "text": "Hey",
  "intent": {
    "id": -8219322614450820822,
    "name": "greet",
    "confidence": 0.9991025328636169
  },
  "entities": [],
  "intent_ranking": [
    {
      "id": -8219322614450820822,
      "name": "greet",
      "confidence": 0.9991025328636169
    }
  ],
  {
    "id": 4345760599580151572,
    "name": "out_of_scope",
    "confidence": 0.00032306340290233493
  },
  {
    "id": -3589040018461778325,
    "name": "goodbye",
    "confidence": 0.0001334369881078601
  }
],
My project is very hard
{
  "text": "My project is very hard",
  "intent": {
    "id": -5544642776888862858,
    "name": "project_tension",
    "confidence": 0.9956598281860352
  },
  "entities": [],
  "intent_ranking": [
    {
      "id": -5544642776888862858,
      "name": "project_tension",
      "confidence": 0.9956598281860352
    },
    {
      "id": -9150908421823239594,
      "name": "stress",
      "confidence": 0.0015480165602639318
    }
  ],
  {
    "id": -4646217258282271999,
    "name": "affirm",
    "confidence": 0.000600550149101764
  }
],
```

**Fig:** Confidence value- greet intent  
Confidence value- project\_tension intent

```

I am amazing
{
  "text": "I am amazing",
  "intent": {
    "id": -5811858462712046098,
    "name": "mood_great",
    "confidence": 0.9989427328109741
  },
  "entities": [],
  "intent_ranking": [
    {
      "id": -5811858462712046098,
      "name": "mood_great",
      "confidence": 0.9989427328109741
    },
    {
      "id": 886731474996725942,
      "name": "bot_challenge",
      "confidence": 0.0003899138537235558
    },
    {
      "id": 4941475330173315714,
      "name": "deny",
      "confidence": 0.00018254132010042667
    }
  ],
}

See you later
{
  "text": "See you later",
  "intent": {
    "id": -3589040018461778325,
    "name": "goodbye",
    "confidence": 0.9965921640396118
  },
  "entities": [],
  "intent_ranking": [
    {
      "id": -3589040018461778325,
      "name": "goodbye",
      "confidence": 0.9965921640396118
    },
    {
      "id": 4137283043473978445,
      "name": "sleep_issues",
      "confidence": 0.0008745818049646914
    },
    {
      "id": -8219322614450820822,
      "name": "greet",
      "confidence": 0.0006255175605510039
    }
  ],
}

```

**Fig:** Confidence value- goodbye intent  
Confidence value -mood\_great intent

5. Hsu C, Lin C. 2002. A comparison of methods for multiclass Support Vector Machines. *IEEE Transactions on Neural Networks*;13:415–425
6. Mooney CZ, Duval RD. 1993. Bootstrapping: A Nonparametric Approach to Statistical Inference. Thousand Oaks, CA: Sage Publications.
7. Saif H, He Y, Fernandez M, Alani H. 2014. Semantic patterns for sentiment analysis of Twitter. In: *The Semantic Web (ISWC)*. Springer; p. 324–340.
8. Smailović J, Kranjc J, Grčar M, Znidaršič M, Mozetič I. 2015. Monitoring the Twitter sentiment during the Bulgarian elections. In: *Proc. IEEE Intl. Conf. on Data Science and Advanced Analytics*. IEEE; p. 1–10.
9. Steven Dow, Blair MacIntyre, Jaemin Lee, Christopher Oezbek, Jay David Bolter, and Maribeth Gandy. 2005. Wizard of Oz Support Throughout an Iterative Design Process. *IEEE Pervasive Computing* 4, 4 (Oct. 2005), 18–26
10. Thakur, M. S. (2017). Review on Structural Software Testing Coverage Approaches. *International Journal of Advance Research, Ideas and Innovations in Technology*, 281-286
11. Yang Li, Jason I. Hong, and James A. Landay. 2007. Design Challenges and Principles for Wizard of Oz Testing of Location-Enhanced Applications. *IEEE Pervasive Computing* 6, 2, 70–75.

**Fig:**

#### 4. ACKNOWLEDGEMENTS

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#### 5. REFERENCES

1. Angela Cora Garcia and Jennifer Baker Jacobs, 1999. The Eyes of the Beholder: Understanding the Turn-Taking System in Quasi-Synchronous Computer-Mediated Communication. *Research on Language and Social Interaction* 32, 4 (1999), 337–367
2. Barbosa L, Feng J. 2010. Robust sentiment detection on Twitter from biased and noisy data. In: *Proc. 23rd Intl. Conf. on Computational Linguistics: Posters*. ACL; p. 36–44
3. Garcia Angela Cora Jacobs, Jennifer Baker. 2013. Repair in chat room interaction. In *Pragmatics of computer-mediated communication*, Susan C. Herring (Ed.). de Gruyter Mouton, Berlin.
4. Holovaty, A., & Kaplan-Moss, J. (2008). *The Definitive Guide to Django: Web Development done right*. Apress