**Title: Connecting Conversation to Care – Positive AI**

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AI is the simulation of human intelligence by machines, enabling them to perform digital tasks like learning, reasoning, and problem solving. Machine learning is the subset of AI that allows systems to automatically learn and improve from experiences without being explicitly programmed. By analyzing patterns in data, ML models can make predictions, detect anomalies, and support decision-making – making it an ideal tool for early detection and intervention in mental health care.

Mental health encompasses our emotional, psychological, and social well-being. It influences how we think, feel, and behave, and plays a role in how we manage stress, relate to others, and make choices. Mental and physical health are equally crucial for overall well-being. The presence of long-lasting physical conditions can also contribute to mental health challenges.

Positive AI refers to the design and use of artificial intelligence systems that actively promote human well-being, emotional balance and personal growth. Inspired by the principles of positive psychology, positive AI aims not just solve problems, but also foster happiness, resilience, empathy, and healthier lives. In the context of mental health, it focus on using technology ethically and compassionately to support early detection, empower individuals and connect them with right care – making AI a force for healing and human flourishing.

**Vision**

Psychology is a fascinating field of understanding the human mind. Without well-being, one can’t truly thrive. Therefore, it’s equally important to consider mental health alongside physical health. This project aims to implement an AI model capable of predicting whether an individual may be experiencing any kind of mental health disorder, enabling early intervention by psychologists through appropriate therapy or psychiatric. With rising cases of depression, bipolar disorder and other mental health disorders are increasing globally – Often influenced by lifestyle changes, social isolation and relationship difficulties. Timely detection is critical at the same time far beyond even for celebrities and highly famous and common man. A well-designed model could play a significant role in preventing suicide, promoting early treatment, and ultimately improving mental well-being.

The vision is to empower people across the world by providing a tool that can identify symptoms through conversations and guide them immediately towards the proper professional help by alerting the medical providers. Let us channel the power of digital transformation for our own balancing and creating happier lives and nurturing creative healthy minds.

**About Dataset**

This dataset is collected from Keggle.com, it has a usability score of 10. And dataset seems to cover a wide range of linguistic, psychological, and behavioral attributes, potentially suitable for analyzing mental health-related topics in online communities or text data. With a wide range of features, including sentiment analysis scores and psychological indicators, the dataset offers opportunities for developing predictive models to identify or predict mental health outcomes based on textual data. This can be useful for early intervention and support.

**Brief description of each column:**

* Timestamp: The date and time when the respondent submitted the survey.
* Gender: The respondent’s gender identity.
* Country: The country where the respondent resides.
* Occupation: The respondent’s job role or profession.
* self\_employed: Indicates if the respondent is self-employed (Yes/No).
* family\_history: Whether the respondent has a family history of mental illness (Yes/No).
* past\_treatment: Whether the respondent has ever sought treatment for a mental health condition (Yes/No)
* Days\_Indoors: How many days the respondent stayed indoors recently, possibly due to external stressors.
* Growing\_Stress: Indicates if the respondent feels their stress levels are increasing.
* Changes\_Habits: Reports any noticeable changes in habits or routines.
* Mental\_Health\_History: Indicates if the respondent has a past diagnosis or history of mental health issues.
* Mental\_Disorder: Whether the respondent experiences sudden or frequent mood changes.
* Coping\_Struggles: Whether the respondent struggles to cope with everyday stress or pressure.
* Work\_Interest: Level of interest or engagement the respondent has in their work.
* Social\_Weakness: Difficulty in maintaining or engaging in social interactions.
* mental\_health\_consultation\_before: Whether the respondent interested to take a evaluation on the same.
* care\_options: Awareness of available mental health care resources or options.
* Target: Mental\_Disorder
* Multi-class classification, class= Medium, Low, High
* Features: ['Gender', 'Country', 'Occupation', 'self\_employed', 'family\_history',

'past\_treatment', 'Days\_Indoors', 'Growing\_Stress', 'Changes\_Habits',

'Mental\_Health\_History', 'Coping\_Struggles', 'Work\_Interest',

'Social\_Weakness', 'mental\_health\_interview', 'care\_options']

* Total of 292364 data is available
* Shape : (292364, 17)
* Duplicates: 1487 (Removed)
* Null values : 5167 – handle later
* Data type is int64 for one column and others are Objects
* Timestamp is not useful to build the model - drop column timestamp

**Dataset**



**Project Environment setup:**

* Programming Language: Python 3.13.5
* IDE: Visual Studio Code (VS Code)
* Operating System: Windows 11 Pro
* Processor: 12th Gen Intel® Core™ i5-1235U @ 1.30 GHz
* Python Libraries : scikit-learn (sklearn), pandas, numpy, matplotlib, seaborn

**Initial Exploratory Data Analysis**

Step 1: Load your data using library and understand your data.

* After loading the data, datatypes are int64 for ‘Days\_Indoors’ and all other columns are object. We have one numerical column and 14 categorical columns.
* Timestamp is the survey submission time, never effects the model – drop timestamp.

Observation 2: Duplicates are removed from the dataset.

Observation 3: Outliers and imbalances

* Fetched the frequency, and checked the data balancing below is the observation.
* Target : Mental\_Disorder, classes and their observations

|  |  |  |
| --- | --- | --- |
| Class | Count | Percentage |
| Low | 74593 | 34.38 |
| High | 67703 | 34.38 |
| Medium | 74670 | 31.20 |

* Features: From the below graph observation are

1. Gender has imbalance – since ‘Male’ has dominating data distribution. Since it’s important but categorical we need to use OnehotEncoding and we will check if it leads bias/dominates prediction later. We can keep this as it is.
2. Self\_employment is 90% No and 10% Yes. Kept it with proper encoding. Let’s see if it balances and model predicts as without domination.
3. Mental\_health\_interview has 75% no, 15% may be, 10% yes – this is corelated with target so we can keep it, since class imbalance doesn’t much effect the prediction.
4. Country – has high imbalance. USA makes 50%+ of the data – so the model can become biased towards patterns from that country. Many countries have few rows, which implies noise. We need to deal with this. For that Group rare countries as other, then use target encoding. Country is strongly related to the country and their culture target mean encoding will help to handle.
5. Days\_Indoors:
6. For Self\_employed – missing values are found. To deal with it – first need to fill it with nan values, since it can’t be able to manage null values and can through error. And then we can use an imputer to fill the value. Decided to use OrdinalEncoder() and then impute with iterativeImputation().