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Mental Health Assist and Diagnosis Conversational Interface using Logistic Regression Model for Emotion and Sentiment Analysis

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Abstract. The aim of this work was to create a fully functional AI-ML based conversational agent that behaves like a real time therapist which analyses the user's emotion at every step and provides appropriate responses and feedback. AI chatbots, although fairly new to the domain of mental health, can help in destigmatizing seeking help, and are more easily accessible to everyone, at any time. Chatbots provide an effective way to communicate with a user and offer helpful emotional support in a more economical way. While making regular psychiatric visits often require a fixed duration/ appointment which can be time consuming and is restricted to a fraction of the day, the proposed chatbot can keep track of your health on the go at any time. The application will have a self-healing kit suggesting various exercises, both mental and physical that the user may implement in his day-to-day life. The study below goes into further detail on the major insinuations for future chatbot agent design and assessment

Keywords: chatbot, sentiment-analysis, machine learning, logistic regression, mental health

1.   Introduction
Chatbots for mental health offer a reassuring presence to service consumers, engaging them in discussion when they are feeling down. The intention of this work was to build an AI chatbot to converse with the user in a constructive way and to suggest helpful remedies. The chatbot provides real time conversational therapy for the user and diagnoses based on a mental health assessment scale called the K10 (Kessler's Psychological Distress Scale) and provides appropriate outputs and feedback.

The AI therapist also performs a mental health assessment test to diagnose the current status of the user's mental health and provides relevant suggestions. An ML model, specifically the Logistic Regression Model was made use of to train a dataset of emotions/text. Sentiment Analysis was performed to categorize the emotions as per the sentiment which will then be used to predict emotion in a more accurate way. Using the above trained LR model, the user's emotion was recognized and the therapist then appropriately probes the user to continue the conversation for as long as the user wishes to. Using the Kessler's Psychological Distress scale, a diagnosis was made to compute a score out of 50 to assess the user's current mental state, following which appropriate replies are formed. Sentiment Analysis was performed on each category of emotions and was further classified into "Neutral, Positive and Negative".

2.   Background

There was a significant gap between the therapy that should be accessible and the aid that was conveniently and cost-effectively available. Even in developed nations, the patient-to-psychiatrist/psychologist ratio was 10000:1. Most people with issues regarding mental health never get the help they seek or require. Many digital interfaces are developing feasible additional services to fulfil various Artificial intelligence-based solutions and are being created in collaboration with healthcare experts to give support and, in some cases, companionship to a person. The cost of mental health diagnosis and treatment might potentially be reduced as a result of this. When it comes to psychiatric problems, most individuals have experienced the stigma that exists in our culture, which frequently prevents appropriate treatment. Chatbots, which are designed particularly to connect with people who are suffering from mental illnesses, have the potential to be valuable aids.

3.   Literature Review

The authors of [1], have reviewed how consumers interact with and are redirected by a depression chatbot(Tess). The first goal was to explain Tess' cumulative use, as well as total number of depression module encounters, typed characters, user comments, and average time spent engaging with the modules. Figuring out how individuals transitioned from one module to the next was the second aim. The third goal was to explain how each module was used by counting the number of user texts, characters written, total use time, and completion rates. The fourth goal evaluated number of objects, time of use, number of messages received, usage patterns and characters used to better understand participant flow within modules.

In [2], the authors studied and reviewed the latest evidence for chatbots, as well as their part in mental illness diagnosis, and care. Chatbots can be useful in delivering therapy for those who are hesitant to share their emotional issues with another human being. Due to this, they arrived at a conclusion that simulated therapy delivered by a chatbot may increase access to mental health care while still being more successful for those who are hesitant to communicate with a therapist.

The writers of [3], summarise and pool the findings of previous studies in order to determine the efficacy and safety of chatbots in improving mental health. The effects of chatbots on the magnitude of anxiety, as well as their positive and negative effects, were mixed. Two experiments looked at the chatbot safety and concluded that they are steady in terms of mental wellbeing, with no records of any adverse effects.

In the paper [4], the authors perform an analysis to define the spectrum of chatbots that promote mental health as well as determine the current condition of the art. The review's main goals are to define the usefulness of chatbots in the medical field, go over the existing information for chatbots in mental health promotion, and put forward the benefits, limitations, threats, and possible difficulties of implementing chatbots in medical field. Chatbot technology is currently in its early stages of growth. By their very essence, most experiments are pilot studies. There is a scarcity of high-quality data obtained from randomised controlled trials in this area. The results in terms of chatbots' practicability,

feasibility, and recognition to promote mental wellbeing are encouraging, but they are not yet explicitly transferable to psychotherapeutic settings.

The writers in their paper, [5], suggest a chatbot for mental health surveillance that aids in keeping track of people's mental health. Depending on the needs of the user, this can be made use of once or twice a week. A series of questions based on DASS-21 will be asked first by the chatbot. If the DASS score is not regular, the programme processes the answers and advances the applicant to the next stage, where he or she will use the camera and microphone to record answers to a new collection of questions about his or her everyday schedule, work life, and family.

In the paper, [6], the authors reflect on some recent studies and early advances on how sophisticated artificial intelligence (AI) approaches can complement the services offered by clinicians and simplify user-customized counselling in order to scale up the MOST model and platform's use.

The authors in their paper, [7], design a concept of a model chatbot that could be made use of in counselling for mental health issues. Mental wellbeing issues are one of the leading sources of illness burden around the world. The disparity between need for mental health services and funding available in the National Health Service (NHS) is expected to increase, necessitating providers to develop more cost-efficient ways to provide mental health care. Anxiety, fatigue, and depression are among the problems for which digital interventions have been developed. Chatbots may be used as isolated interventions or as part of a digital intervention. The chatbot was expected to aid with initial counselling while also directing patients to the appropriate facilities or self-help material.

4.   Initialization
4.1.   Initial Procedure
This project that was built in python involved the use of the following libraries: pandas (for reading and updating the dataset), numpy (for basic array creation and use), neattext (for text cleaning), seaborn (to visualise data and plot graphs), textblob (for performing sentiment analysis on the dataset).

The dataset, initially consisted of 34,792 rows of sentences and 2 columns - Emotion and Text. After performing relevant checks on the dataset regarding null values and types, a value count of the emotions in the dataset were obtained and were as shown in Table 1:

Table 1. Numerical data of the texts classified for each class of emotion.

Emotion	Value Count
joy	11045
sadness	6722
fear	5410
anger	4297
surprise	4062
neutral	2254
disgust	856
shame	146

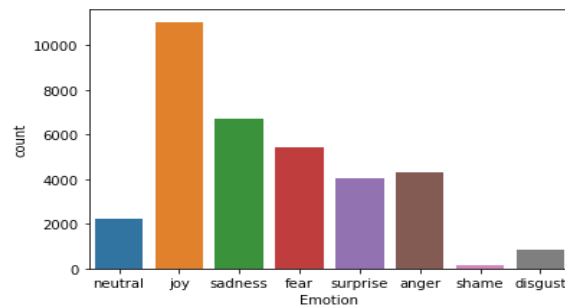The above data, when plotted using Seaborn library was visualized as a plot shown in Figure 1 :

Figure 1. Plot of the number of texts for each class of emotion

The emotion recognition procedure was then done. Firstly, Sentiment Analysis was performed on the above dataset before any Preprocessing/Text Cleaning. This was done because Text Cleaning removes a lot of unnecessary text which could have played a role in determining the sentiment and may also have led to text becoming a NULL value which cannot be passed for further sentiment analysis.

TextBlob is made use of to determine the sentiment of the text in the dataset. Using TextBlob, 3 classifications can be made - Positive, Negative and Neutral. Making use of the function "blob.sentiment.polarity" which returns a value in between [-1,1], the "get_sentiment" function is created to perform the above mentioned classification. This leads to the addition of a third column - Sentiment, that contains the values returned from the "get_sentiment" function for each of the text values passed.

The Emotion and Sentiment from the now obtained dataset were compared and grouped together for visualization as depicted in Table 2 and Figure 2.

Table 2. Sentiments obtained for each class.

| Emotion	Sentiment	Value Count
anger	Negative	1787
	Neutral	1386
	Positive	1124
disgust	Negative	325
	Neutral	249
	Positive	282
fear	Negative	1534
	Neutral	1843
	Positive	2033
joy	Negative	1682
	Neutral	3648
	Positive	5715
neutral	Negative	178
	Neutral	1523
	Positive	553
sadness	Negative	2630
	Neutral	2127
	Positive	1965
shame	Negative	46
	Neutral	50
	Positive	50
surprise	Negative	623
	Neutral	1545
	Positive	1894
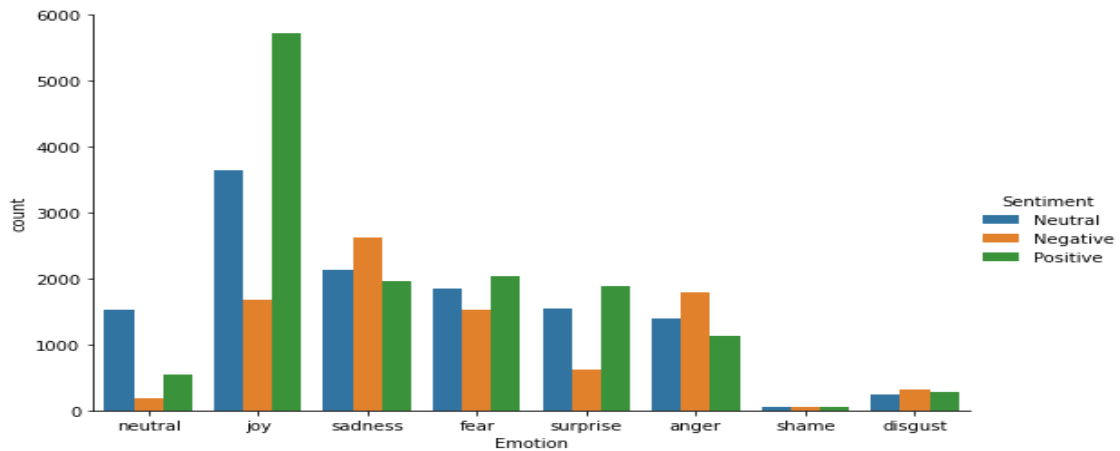
Figure 2. Graph depicting neutral. negative and positive sentiments for the texts of each class

4.2.   Text Cleaning

Preprocessing on this dataset led to the addition of a fourth column - Clean_Text. This column is obtained by making use of the "neattext" library, to remove stopwords, user-handles and punctuations from the existing text in the dataset.

4.3.   Text Classification

Using the "sklearn.linear_model" library, the Logistic Regression model was called. The dataset obtained from the above procedures is split using XFeatures for "Clean_Text" and ylabels for "Emotion" into train and test variables. The Logistic Regression model was then built and the X_train and y_train variables were fit into the model.

A function "predict_emotion" was created to first, vectorize the passed parameter for sample text. Next, lr_model.predict accepts the above vectorized data and predicts the most probable class of emotion.

5.   Methodology

5.1.   Architecture

Figure 3 below showcases the basic architecture of the chatbot being implemented. The user's response is passed through the trained Logistic Regression (LR) Model that was made use of to predict the user's emotions from the text using the "predict_emotion" function.The classified emotion is then returned to the Response Generator which searches for the matching class of emotion out of the 8 defined emotions and retrieves unique responses for the class of user-predicted emotion. The response retrieved is displayed and the user is further probed based on his/her replies until he/she chooses to quit. This showcases the basic architecture of the chatbot implemented.
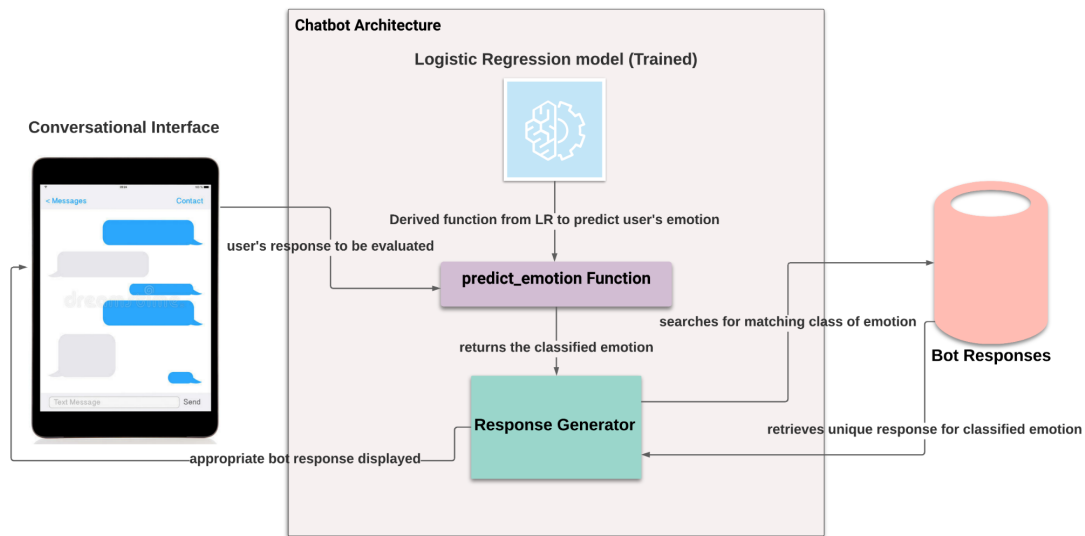
Figure 3. Architecture diagram of the AIML chatbot

5.2.   Detailed Steps

A dataset of emotions/text was trained using an ML model, specifically the Logistic Regression Model. Logistic Regression (LR) model was chosen as it was best at making predictions based on categories/groups of data, as is the case here with the 8 emotions that were chosen. When there were several explanatory variables, logistic regression was employed to calculate the odds ratio. Sentiment Analysis was used to categorise emotions based on their sentiment, which was subsequently used to better accurately anticipate emotion. Sentiment Analysis was performed on each of the 8 emotions to further categorize them into "Positive", "Negative" and "Neutral". Based on the classifications made, the user's input was passed into the "predict_emotion" function designed to identify the most probable emotion out of the eight. The "predict_emotion" function was an author-defined function which identified the most probable emotion for the string that was passed as an argument. The function value that is returned from this was made use of to pick out appropriate responses. This was done in accordance with the established emotions from a pool of responses formulated by the authors with reference to generic therapist replies. The user's emotion was identified using the above-mentioned trained LR model, and the therapist then probed the user to prolong the discussion for as long as the user desired. A diagnosis was established using the Kessler's Psychological Distress scale to calculate a score out of 50 to measure the user's present mental condition, after which suitable responses were generated.

The final step in implementation was to make use of the above trained LR model and its "predict_emotion" function to form a conversational interface. The chatbot first begins with a greeting to welcome the user and accepts the name/nickname of the user and addresses the user accordingly through the conversation. The conversational bot then proceeds to probe the user about the various activities of their day, based on whose replies, an analysis was performed at each step of the conversation for which an emotion was predicted by the lr_model, depending on which the therapist bot provides appropriate responses and probing questions to further engage the user in the conversation.

When the user decides to quit the conversation, the bot then asks the user if they would like to take a diagnosis test before they leave. If the user agrees, the bot then proceeds to list out 10 questions chosen from the Kessler's Psychological Distress (K10) Scale. Logistic regression was used to obtain odds ratio in the presence of more than one explanatory variable to evaluate the user's choices for each question and produce a final score out of 50 which will then be utilised to assess the intensity of the aid

required. The bot then provides appropriate responses and suggestions to help the user overcome his/her current situation.

6.   Data and Results
6.1.   Dataset Details
The dataset used consists of 34,792 tweets, which is the same as the initial dataset considered.Each tweet in the dataset is classified into a set of 8 classes of emotions - joy, sadness, neutral, anger, shame, disgust, surprise and fear; as shown in Table 3. This was made use of to train the LR model which was then later used to classify user text into emotions.

Table 3. Sample table of the raw Dataset.

Emotion	Text
joy	Sage Act upgrade on my to do list for tomorrow.
sadness	Couldn't wait to see them live. If missing them in NH7 wasn't painful enuf, Suraj 's performing his last gig in delhi.
fear	I'm expecting an extremely important phone call any minute now #terror #opportunity
anger	My parents didn't allow me to go to a social function that all my friends were attending.
surprise	I almost forgot my hair was red until I looked in the mirror
neutral	Why?
disgust	ewww she got that nasty ass default like she cute
shame	Nobody doubted him , or failed to recognise his temporary financial embarrassment .

The dataset was then passed through Sentiment Analysis and later, cleaned to remove irrelevant text, such as user-handles, stopwords and punctuations. Two new columns called "Clean_Text" and "Sentiment" were then added after performing all the pre-processing and Sentiment Analysis respectively. Figure 4 shows the dataset after the same.

Emotion	Text	Clean_Text	Sentiment
neutral	Why ?	NaN	Neutral
joy	Sage Act upgrade on my to do list for tommorow.	Sage Act upgrade list tommorow	Neutral
sadness	ON THE WAY TO MY HOMEGIRL BABY FUNERAL!!! MAN ...	WAY HOMEGIRL BABY FUNERAL MAN HATE FUNERALS SH...	Negative
joy	Such an eye ! The true hazel eye-and so brill...	eye true hazel eyeand brilliant Regular feat...	Positive
joy	@Iluvmiasantos ugh babe.. hugggzzz for u .! b...	ugh babe hugggzzz u babe naamazed nga ako e...	Neutral

Figure 4. Dataset after pre-processing and Sentiment Analysis

6.2.   Keyword Extraction
In this section, the most commonly occurring words per class of emotion was extracted for visualization purposes. For example, for the emotion class "**joy**", after extracting the most common words, they are put into a document called "**joy_docx**" and using this, a plot was created using WordCloud library as shown in Figure 5.

Figure 5. Wordcloud plot visualizing the most common keywords extracted for the class 'joy

6.3.   Model Evaluation

Using the trained LR Model, a classification report was generated as shown in Figure 6. The precision as shown in Figure 6 was averaging to about 0.62 which is the best case for therapeutic conversations. The confusion matrix was generated as shown in Figure 7.

Figure 6. Classification report of the LR Model

Figure 7. Confusion matrix for the LR Model

6.4.   Inference

The model was able to successfully identify each of the 8 emotions based on the user's inputs. Compared to the previously used Naive-Bayes model on the above dataset, the accuracy of the LR model turned out to be greater, increasing the precision of the predictions made. The accuracy of the LR model was found to be 0.62 compared to the Naive-Bayes model that provided an accuracy of 0.56. As mentioned in [8], LR gives a better accuracy on larger datasets, as is the one used above, than Naive Bayes. The chatbot that was implemented with this LR model generated appropriate replies almost instantly.

6.5.   Chatbot

Figure 8. Code snippet of the initial conversation with the user

In Figure 8, the initial conversation of the bot with the user is shown. Here, the bot gathers the name and nickname of the user and proceeds to ask the user about their current mental health status through a general question. Based on the user's reply to this, the bot then replies with either an affirmative message or a reassuring reply.

Figure 9. Code snippet of the user being engaged in conversation by the bot

In Figure 9, the bot proceeds to engage the user in a conversation, so as to get the user to express their emotions and/ or problems and provide appropriate responses for the same. The responses are selected from a poll of responses after the emotions of the user's replies are predicted.

Figure 10. Code snippet of the diagnosis test K10

Figure 11. Code snippet of the result of the diagnosis done by the bot along with its reply

The final step is the "assessment" which proceeds as shown in Figure 10 and 11. The chatbot proceeds to ask the user if he/she wants to take the diagnosis test after he/she wishes to quit the conversation. Depending on the user's response, the chatbot continues with the assessment or ends the conversation with a concluding statement.

The diagnosis consists of asking the user 10 questions about their current mental health status over the past few weeks. Once the user answers all of the questions, depending on the options they picked, the bot calculates a final score out of 50 depicting the extent of seriousness of the user's mental health status. According to the score, the chatbot then suggests the user to seek external help/provide motivational feedback if they are doing better than usual. Finally the chatbot concludes the conversation asking the user to come back later and interact with the bot and re-assess themselves.

7.   Future Discussions

In addition to treatment, AI-ML technology has the possibility of improving mental health and well-being in a more general sense. In order to truly foster sharing, transparency, and self-reflection, having an actual conversation puts you in a different mindset. AI conversational agents, although can help guide or uplift a user's moods, do have some concerns to be addressed. Because health-related information may be communicated through emotional chatbots, (e.g., revelation of illnesses and mental problems), it's vital to keep in mind that chatbots must follow regulations regulating the adoption of suitable data protection and security safeguards.. Authentication for each user can be provided to further aid the user as well as to overcome concerns regarding privacy of the data being provided.

8.   Conclusion

AIML based chatbots can effectively provide aid to even the most remote users that are seeking help and destigmatize the concept of getting help, by helping them reach out for assistance from the comfort of their homes. There is a scarcity of human therapists, and they are not available 24 hours a day, seven days a week. They're also not available in rural areas, and individuals are often unwilling to seek mental health care because of the stigma associated with it. For these reasons, there are advantages to utilising AIML since it is always available, regardless of where you are, and it has no stigma attached to it. People are more ready to open up to an AI than they are to an online form on a self-help website that is more like a textbook. In order to truly foster sharing, transparency, and self-reflection, having a meaningful conversation puts you in a different mindset. A machine learning model, specifically the LR model, was employed to build this chatbot, as this seemed to have a more diverse response system compared to, for instance, chatbots built with RasaNLU where certain responses would end up looped. Chatbot research is in its early phases, and while studies suggest that while chatbots can be useful, more knowledge on how they operate is needed.

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