Dost-Mental Health Assistant Chatbot

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Abstract:
Mental health is a topic that is still new and must be introduced to everyone with tremendous care and caution and slowly made mainstream, so people don't view it as taboo and get appropriate treatment from professionals. Until then, chatbots will play an integral part in mental health assistance, for citizens who can't afford expensive treatments. The main aim of this paper is to introduce a mental health assistant, Dost, a chatbot built on Rasa framework and deployed on Telegram. The aim is to understand the user's problems and proceed to suggest ways to improve the user's condition through daily, casual conversations. Chatbots will play an integral role in the future of healthcare, to make mental health facilities accessible to everyone, from students to senior citizens and offer 24/7 assistance in the absence of doctors.

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SECTION I.
Introduction

Chatbot is a software which has the power to converse with a human in a natural way. They are used across many different scenarios and have quite a few applications in various industries. Chatbots use artificial intelligence (AI), natural language processing (NLP) and other Machine Learning models to understand the input given by its users in formats like texts, graphics, or speech. Chatbots have the power to simulate natural human conversations and in some cases, run simple automated tasks.

Mental health deals with our emotional, psychological and social well-being and affects how we think, how we interact with others and how we regulate our emotions and feelings. It is equally if not more important as is our physical health and it is high time people started viewing it that way. Mental health is usually treated by mental health professionals by making use of psychotherapy or pharmacotherapy. However, with little to no infrastructure available for assistance to people suffering from mental disorders in most parts of the world, the use of a mental chatbot comes in as a saviour in certain situations with studies showing that by making use of AI powered chatbots, the improvement in the mental health of its users is too substantial to be overlooked. A chatbot provides an interface where its users can freely talk about their emotions and feelings without having to worry about anyone judging them or nullifying their sufferings. It can help provide an e diagnosis of any mental disorder that its user might be going through and provide remedies for the same ask the user to refer to a mental health professional if it is beyond its scope. Chatbots will never replace therapy or therapists but it will make therapy more accessible and will in turn help therapists immensely.

Currently, there are various kinds of chatbot assistants available in the market like Google Assistant, Siri, Alexa, etc. but they are built to perform everyday tasks and to help their users automate tasks to improve their digital experience. Although mental health assistants exist, they are not so advanced yet and provide a good area for research and development.

India does not have an advanced and accessible mental health infrastructure to cater to the mental health epidemic that is caused by the ongoing COVID-19 pandemic. As of 2021, 20% adults in India suffer from varied mental health disorders, with negligible or no support and clinical treatment. The economic loss thanks to psychological state conditions between 2012–2030 is estimated to be USD 1.03 trillion in India, consistent with WHO 2020 report [16]. Upon more investigation and discussion among peers, the most recurrent mental health issues that young adults are facing in the new normal are depression, anxiety, stress, post-traumaticstress disorder (PTSD) and attention deficit/hyperactivity disorder (ADHD). With mental health deteriorating at a very high rate, there is an urgent need to take long-term and sustainable actions to improve the mental health of young people and adults alike.

This paper introduces, Dost, a mental health assistant built using Rasa framework and is deployed on Telegram, which makes it easy to access therapy and assistance, or simply a listening ear for when one is in need of a friend. Upon creating a database of mental health FAQs, referring to Mental Health FAQs for chatbot from Kaggle, and added a significant number of new intents to make the bot more robust and user friendly. It will understand the context of the user's query and will try to respond with an appropriate reply which will help aid the user in whatever difficulty they are facing regarding their mental health.

SECTION II.
Related Work

Divya Madhu et. al. [1] describes an idea and a set of features that would make a medical chatbot address the issues regarding the current situation of the field of medicine. A lot of medicines are being made by various companies to treat various diseases and it is crucial for the consumer to know the composition and dosage type to ensure that they are taking not only the right medications for their health conditions but are also taking it in the right amounts. There is a signature for each disease. These signatures can start as small problems and grow into something dangerous and life altering [1]. With the right analysis of a person's physical and mental state, we can predict any problem that may be harmful to them before it actually starts causing the damage. The system that given the name and manufacturer of the pharmaceutical, the suggested can describe it. It will provide information on the chemical make-up, dose for each age group, recommended usage, adverse effects, etc. Users are able to inquire about practically any aspect of the medication, and a doctor's opinion can be confirmed based on that information. [1]. Other important features would be to make the chatbot available across any operating software in order to make it available to a wide spectrum of users. Apart from that the system should be easy to upgrade and new modules should be easily integrated into the existing system.

Attention deficiency is one of the growing problems in adults, and early diagnosis and nursing are required. Chatbots based on Mobile delivering Cognitive Behavioural Therapy and psychoeducation have been used for symptomsreduction and treatment in other mental illnesses. [2] Sooah Jang et al. [2] studied and investigated the feasibility and practicability of a short-term interactive chatbot application. It was a randomized study involving 43 participants having attention deficit, ageing 19–60, spanning 4 weeks in which 23 participants made use of a chatbot app called “Todaki”, while the remaining were given books on managing attention deficit. After the experimental study, it showed decreasing levels of attention deficiency in the group using the chatbot and helped identify the feasibility of a mobile-app based chatbot to enhance attention deficiency and its associated clinical psychiatric signs and symptoms. [2]

SERMO is a mobile application built and introduced by Sooah Jang et. al. [3] to address the issue of lack of resources delivering mental health assistance. It implements methods of Cognitive Behavioural Therapy in order to support mentally unwell people in regulating their emotions and handling with their thoughts and feelings. SERMO aims to understand user emotions using natural language input and the developers have made use of a lexicon-based approach to help identify emotions of the sentences. Although lexicon-based algorithms fail in capturing the context of the sentence, due to lack of training data in German to implement other algorithms such as SVM or Naive Bayes, the lexicon-based approach was chosen. [3] SERMO studies a user statement to choose an appropriate, instigating or encouraging response when given a particular user emotion. We should confirm the emotions recognized by SERMO by the user, which can be used to gather data. [3]

Y. C. Lee et al. [4] designed and implemented a chatbot that offers 3 chatting styles; they also conducted a study with forty-seven participants where each participant had to experience, the chatbot's feature of self-disclosure at different levels. The participants were later introduced to a mental health professional, after using the chatbot for a few weeks. The participants were asked if they would comply sharing their self-disclosure material with the assigned mental health professional. The participants had the option of editing their content if they chose to share. After Comparing the self-disclosure data of all the participants, the results showed that, inside each group, even after sharing with the mental health professional, the depth of participants' self-disclosure to the chatbot remained almost the same. Through a more self-disclosing chatbot, the participants disclosed more personal information to the mental health professional. Additionally, it was discovered through conversation log analysis that some of the participants changed the content of their self-disclosed material before sharing it with the experts [4]. This work further specifies empirical evidence of various self-disclosure practice, in the way that or accumulating content, that users can take before sharing their self-disclosure to a chatbot alongside a mental health professional.

Chatbots are one of the subsequent models of bots that can make conversations among customers and they are adaptable at the same time. S. Pola et al. [5] developed a chatbot to get additional information from the user and their present state of mind. They presented a model that can detect seven types of emotions from the user's inputs. They have Recurrent Neural Network (RNN) and Long-Short-Term-Memory (LSTM), two important deep learning classifiers, were added to glove2, a pre-trained weighted word index, for improved performance and accuracy [5]. They have also applied hyperparameter tuning for better models and also to avoid overfitting of the model. The results that were observed while training gave an accuracy of 88% and testing gave an accuracy of 84% [5]. In particular, the chatbot's proposed technique is space explicit, where the chatbot would make an effort to thwart sceptic efforts and revive more practical considerations.

K. Deepika et al. [6], presented a jollity chatbot that can talk with humans and can make sure that the chatbot can entertain and give suggestions. To implement this jollity chatbot, they have used Rasa, an open-source conversational AI framework that is also very easy to customize [6]. In this proposed method, they have added 12 intents with each having more than 8 text examples comprising a total of 100 input samples in nlu.md and their response in domain.yml. Jollity chatbot can act as a virtual friend for any user at any time he needs it, particularly all along his depressed occasions by suggesting videos, editorials, articles, and images to make him feel better [6]. This method proves to be cost-effective as it can replace a costly psychological session required to make someone cheerful. The exploratory results of the proposed method show that it can identify the intents and fetch the appropriate replies alongside an precision of 90%.

D. Lee et al. [7] introduced a chatbot application that provides mental health care counselling service based upon natural-language-processing (NLP) and emotion recognition in their paper. The key applications are not very different yet, so healthcare applications could be studied in addition to the intelligent assistant services. The average accuracy of emotional classification was 67.52% for the seven emotional states of surprise, anger, disgust, sadness, fear, and neutrality [7]. It clearly recognizes facial expressions well. The paper illustrated its model on the SFEW2.0 dataset for the EmotiW2015 challenge [7]. They had a setup of 4 levels of hierarchy to recognize a person's emotions and understand natural language input sentences. The bot continuously monitors the user's emotional changes and responds intelligently and sensitively instead of pre-stored stock responses. The bot was able to sense emotional flow through continuous conversations and extract the user's intention to give responses that are sympathetic, informative, etc.

SECTION III.
Method

By developing this chatbot, the aim is to cater to all kinds of queries related to mental health, assistance related to mental health like seeking therapy and other solutions as well as some questions regarding some of the most common mental diseases like anxiety, depression, etc.

Fig 1. - Rasa framework architecture

Fig 1.
Rasa framework architecture

A. System Architecture Description

The proposed chatbot is a contextual AI chatbot which is built using the Rasa library. The NLU model uses training data which comprises intents, entities and responses to understand a user query and to correctly answer from one of the responses available in the training data. Sentences with similar purposes are grouped together to form an intent. For instance, "What is mental health?", "What do you mean by mental health?", come under the intent mental_health_query. Intents are basically verbs in a given sentence.

Now, in order to respond to the user, the bot makes use of stories which are explicitly defined by us while training the model. The stories comprise sets of questions and appropriate responses for the bot to reply with the correct message to the user. The domain file mimics the interactions which users might make with the chatbot. It describes a list of all the intents, entities, actions and slots.

The basic flow of the chatbot would be accepting the user query, extracting and classifying the intents and entities from the query and then choosing an appropriate message to reply with based on the training data and the stories defined by the developers.

B. Model Implementation

The rasa chatbot follows what is called an NLU pipeline which is present in the 'config.yml' file. It basically describes the flow of the that will be used by Rasa to extract and classify intents and entities from the user input. The input is simple text and it is parsed through various components until the intents and entities that it beholds are extracted.

Fig 2. - Natural language processing pipeline [8]

Fig 2.
Natural language processing pipeline [8]

The components are as follows:

1. Tokenizers
2. Featurizers
3. Intent Classifiers
4. Entity Extractors

Tokenizers: For our model, we have made use of the WhiteSpaceTokenizer which is commonly used when the text input is in English Language. The tokenizer's job is to split the user input into a list of words or tokens and in no way does it change or alter the underlying text as shown in Fig 3.

Fig 3. - Tokenization [8]

Fig 3.
Tokenization [8]

Featurizers: The job of a featurizer is to assign each token a numeric value which has some meaning so that it can be fed to the machine learning model as depicted in Fig 4. The use of the LexicalSyntacticFeaturizer which generates window-based features useful for entity recognition and the RegexFeaturizer which vectorizes the user input using regular expressions.

Fig 4. - Featurization [8]

Fig 4.
Featurization [8]

Intent Classifier and Entity Extraction: Once the user input is tokenized and featurized, it is passed to the intent classification model. In our model, we have used the DIETClassifier which not only extracts and classifies intents but also entities. It has the ability to learn from both the tokens as well as the sentence features. This process is shown in Fig 5.

Fig 5. - Intent classification [8]

Fig 5.
Intent classification [8]

The components in the Rasa pipeline are dependent on each other and thus it is executed in a linear sequence. Whenever a user inputs an utterance, Rasa keeps track of it via the 'message' object which passes through all the steps in the rasa pipeline as described in the config.yml file. After each step in the pipeline some additional information gets attached to the message object as shown in the figure below.

Fig 6. - Message object on different stages of the nlu pipeline [8]

Fig 6.
Message object on different stages of the nlu pipeline [8]

C. Prediction of Output

The NLU pipeline gives the intents and entities as the output but does no job of making a prediction of the output to the given textual input. That job is assigned to the Policy pipeline. The policy pipeline makes use of the output gained from the NLU pipeline and also the state of the conversation thus far to make a prediction as to what action must be taken in response to the user input. It comprises of three policies:

1. RulePolicy: This determines the output based on the rules that are predefined by us in the 'rules.yml' file. It handles conversations by matching the rules that are explicitly defined by the developers.

2. MemoizationPolicy: Similar to the rule policy, this handles the conversations based on the predefined stories that are defined by the developers in the 'stories.yml' file.

3. TEDpolicy: This uses machine learning to predict the next best action.

These policies act based on the priorities which are defined by the hierarchy in which they are defined in the policy pipeline. The output of the policy pipeline is a response that best fits the user input.

Fig 7. - Rasa policies [8]

Fig 7.
Rasa policies [8]

D. Fucntional Requirements

The Frontend Part of the project is the part that will appear to the end user, which means the user will entirely communicate through this. The Frontend will be the Telegram application where we will be hosting our chatbot so that it is easily accessible to most users via their mobile applications or by making use of the telegram web application on their desktops. The Telegram application provides a well-developed UI that most users are familiar with and is standard across its platforms. The interface is shown in Fig 8(a) and (b) below.

Fig 8(a). - Demo of chat interface in telegram

Fig 8(a).
Demo of chat interface in telegram

Fig 8(b). - Demo of chat interface in telegram

Fig 8(b).
Demo of chat interface in telegram

Table

Backend Subsystem
In the Backend of our proposed project, Rasa is used as the framework to develop the chatbot logic. In order to install Rasa, we will be using Conda to install various packages. A development environment will be created using Conda and then the project dependencies will be installed within that development environment. The Backend module will be loaded when the user opens the chatbot in the Telegram application. The backend module is not loaded by default and is loaded only when the frontend makes a function call to the backend.

SECTION IV. Results

The chatbot proposed in this paper, is implemented in the Rasa framework. Theproposed and developedMental Health Assistant Chatbot, Dost, is deployed on Telegram using 'botfather' bot. Various evaluating measures like intent accuracy, confusion matrix isused to evaluate the robustness of the system. The number of intents rightlyrecognized by the system is given by equation I.

$$1.\text{Intent Accuracy} = \frac{\text{No. of intents correctly identified}}{\text{Total no. of intents}}$$

View Source

Consider 4 set of 20 random intents, and a total 80 intents. Suppose, the Dost bot classifies 2 intents rightly, a score of value 0.1 will be added, or else a value of 0 will be added. All rightly classified intents are arranged on the diagonal of the created confusion matrix. This makes the authorsevaluate the failures efficiently as the incorrectly classified intents are situated out of the confusion matrix diagonal values.

Table 1. Confusion Matrix showing the accuracy of the intent identification. Information on Mental Illness intent shows an accuracy of 90%, Treatment intent shows an accuracy of 70%, Self-help intent shows an accuracy of 80% and Psychological Terms intents shows an accuracy of 84%.

Fig 9. - Intent prediction histogram

Fig 9.
Intent prediction histogram

Rasa has an intent prediction feature which helps to recognise the intent prediction accuracy of the chatbot. It shows the confidence level of the intents predicted correctly and wrongly, as shown in the above figure.

From experimental results, it is proved that the proposed metal health assistant chatbot is able to achieve an accuracy of 83.5%. It is able to successfully identify the different disorders users are facing and guide the conversation accordingly by giving self-help materials and answering queries related to mental health. It is noted that most users are looking for a friend to talk to, judgement free, and this chatbot fills that gap.

SECTION V. Conclusion

The use of chatbots is increasing in various domains and it is observed that healthcare is the most important field where this technology can have a positive impact. Existing chatbots are mostly rules-based and the major drawback is that there is no scope for further improvement without having some form of human intervention. Based on the literature we reviewed, we were able to conclude that AI powered chatbots prove to be more effective than rules-based chatbots at least in the field of Mental Healthcare. Conversational mental health chatbots are mostly based on emotion recognition methods like sentiment analysis. After doing a fair bit of research we conclude that the area of mental health chatbots is still raw and needs quite a bit of curating in order to be qualified for professional use.

Dost chatbot basically aims to cater different queries related to mental health, assistance to users with mental health ailments like seeking therapy and other solutions as well as some questions regarding some of the most common mental diseases like anxiety, depression, etc. The proposed chatbot is a contextual AI chatbot which is built using Rasa and is deployed on Telegram. This bot is free of cost and very convenient to use since it is available throughout the day.

Confusion matrix and intent accuracyare the parameters based on which our system is evaluated. Based on the experiment's results, it can be said that the chatbotwas able toidentify the intents and can provide the appropriate responses with an approximate accuracy of 83.5%.

There is a lot of room for research ranging from the choice of the algorithms to be used to the level and quality of responses to be given by the chatbots. In the future, we can add various chatting methods like speech to text.

Authors

Figures

References

Citations

Keywords

Metrics