Intelligent System to Foster Mental Health

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Abstract - The state-of-the-art rule-based online therapy bots do not provide users with the experience of talking their emotions out, as in the case of real-time therapy. Instead they have to answer a series of multiple-choice questions, after which the system detects the mental state of a user and provides non-engaging tasks. We propose an intelligent therapeutic chatbot system that provides the user experience and detects mental state from user responses, provides textual therapy and recommends motivational videos depending on the state. The application facilitates user experience by utilizing three models namely, Support Vector Machine (SVM) model for intent recognition, Long Short-Term Memory (LSTM) model for mental-condition classification and Naive Bayes for user feedback classification. We additionally provide content and collaborative-based recommendation on motivational videos using Neo4j. This approach provides better user experience and eliminates any privacy issues.

***Key Words*: Online Therapy, Chatbot, Machine Learning, Neo4j, User Similarity, Mental Health**

1.INTRODUCTION

The mental health of a person affects his/her feelings, thoughts and behaviour. People often struggle to talk about mental health, as they have the fear of being left out or being treated differently. The state-of-the-art online therapy bots facilitate therapy through fixed question answering scenarios where users can respond only through the given options for a question, followed by providing non-engaging tasks, which do not present a choice to the users to talk about their emotions. Thus, it does not provide an actual patient-therapist conversational experience. The covid'19 pandemic has added to the fear of contracting the virus and stress due to the financial crisis. The rate of suicidal tendencies has increased vastly and so, providing online therapy through texts and videos are essential now more than ever.

We propose an intelligent therapeutic chatbot to identify a user's mental state wherein first the response of the user is given to a machine learning classifier to predict the mental state, after which the chatbot provides condition-specific therapy via textual responses and motivational videos to the users. We intend to provide better patient-therapist experience through the conversational chatbot.

2.RELATED WORK

Current intelligent therapy-based systems include ruled-based chatbots that provide textual therapy. Woebot [1] is a conversational chatbot that envisions cognitive behavioural therapy (CBT) with an evidence-based approach to therapy. Users are asked a fixed set of questions, to which they reply by choosing from predefined options, and are provided with tasks. Chatbots like Alice and Eliza [2] communicate with users to serve as a friend who initiates conversation. Inspired by these chatbots, the current chatbots have a wide range of uses, including e-commerce, medical health care, and intelligent tutoring systems. Our motivation for the project is derived from the fact that current bots do not provide conversational patient-therapist encounters, as well as the absence of therapy through motivational videos which can be more engaging, compared to simple tasks.

3.PROPOSED SYSTEM DESIGN

The design comprises four components. The key components are the Support Vector Machine (SVM)[3] model for intent recognition and Bi-directional Long Short Term Memory(Bi-LSTM)[4] model (Fig.1) for mental-state recognition, both of which are implemented using TensorFlow. The two steps in processing the dataset for training the models are tokenization and vectorization. The output from the Bi-LSTM model is then given to a random response generator which is then sent back to the user through a server. Users provide feedback based on the therapy they received which is then fed into a Naive Bayes classifier, which categorises the feedback as positive or negative. The following component is the recommendation engine which is implemented using neo4j. Two types of video recommendations utilized within the system are the content-based recommendation and collaborative-based recommendation. Content based recommendation is utilized to provide videos to the user based on rating. Based on the audit of responses by the user, collaborative based recommendation is used which implements the notion of user similarity.

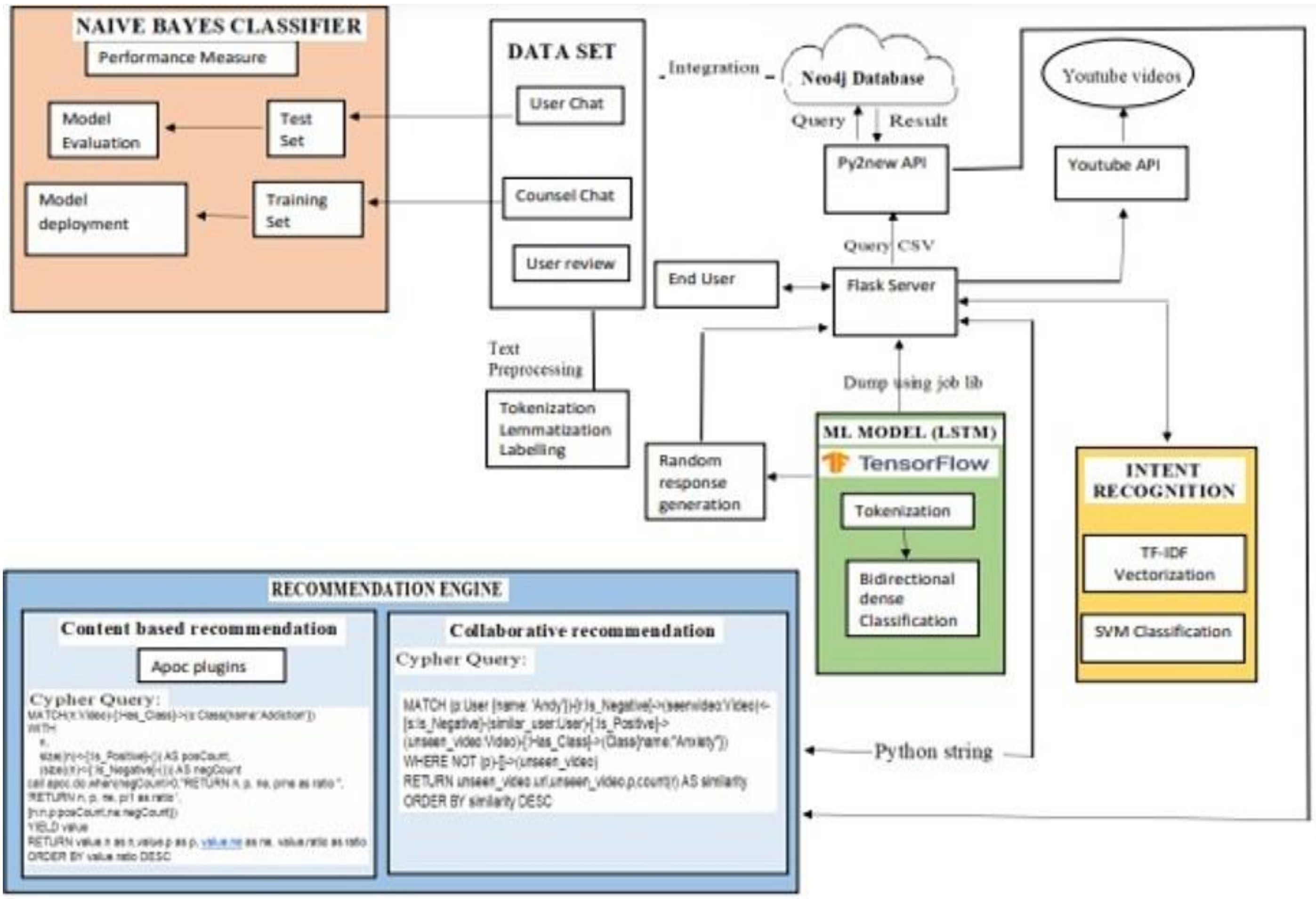

Fig -1: Architecture

4. CHATBOT WORKFLOW

The chatbot initially communicates with the user and obtains the input. We have an intent recognition system that can detect four different types of intents namely greetings, therapy, video and exit. We query more about the user in the event of "greetings", and if the intent is "exit", we stop the conversation. If the intent is "therapy", the chatbot will communicate more until enough data is available to classify the user's mental state. The mental state classification system receives this textual input. If the projected category is a major one, such as suicidal tendency, we advise the user to speak with someone or seek the advice of a professional. If it's a minor category, such as depression or anxiety, we offer motivational texts and, additionally with the help of the Neo4j recommendation model, we offer motivational videos to users and ask for feedback so that using collaborative-based recommendation, similar people can benefit in the future.

5. PROPOSED SYSTEM IMPLEMENTATION

5.1 Dataset Collection and Preprocessing

The datasets which we used were:

1)Counselchat-data:

There are 31 topics on the dataset[5] including “depression”, “military issues”, etc. The dataset had some repetition of questions and answers which we have cleaned during the pre-processing stage. The dataset is presented as a CSV file with 10 columns: questionID ,questionTitle, questionText , questionLink, topic ,therapistInfo, therapistURL, answerText, upvotes, split. Generally, most questions have few responses. It consists of pretty short questions and long answers. We utilized the user responses and their corresponding mental-state as attributes.

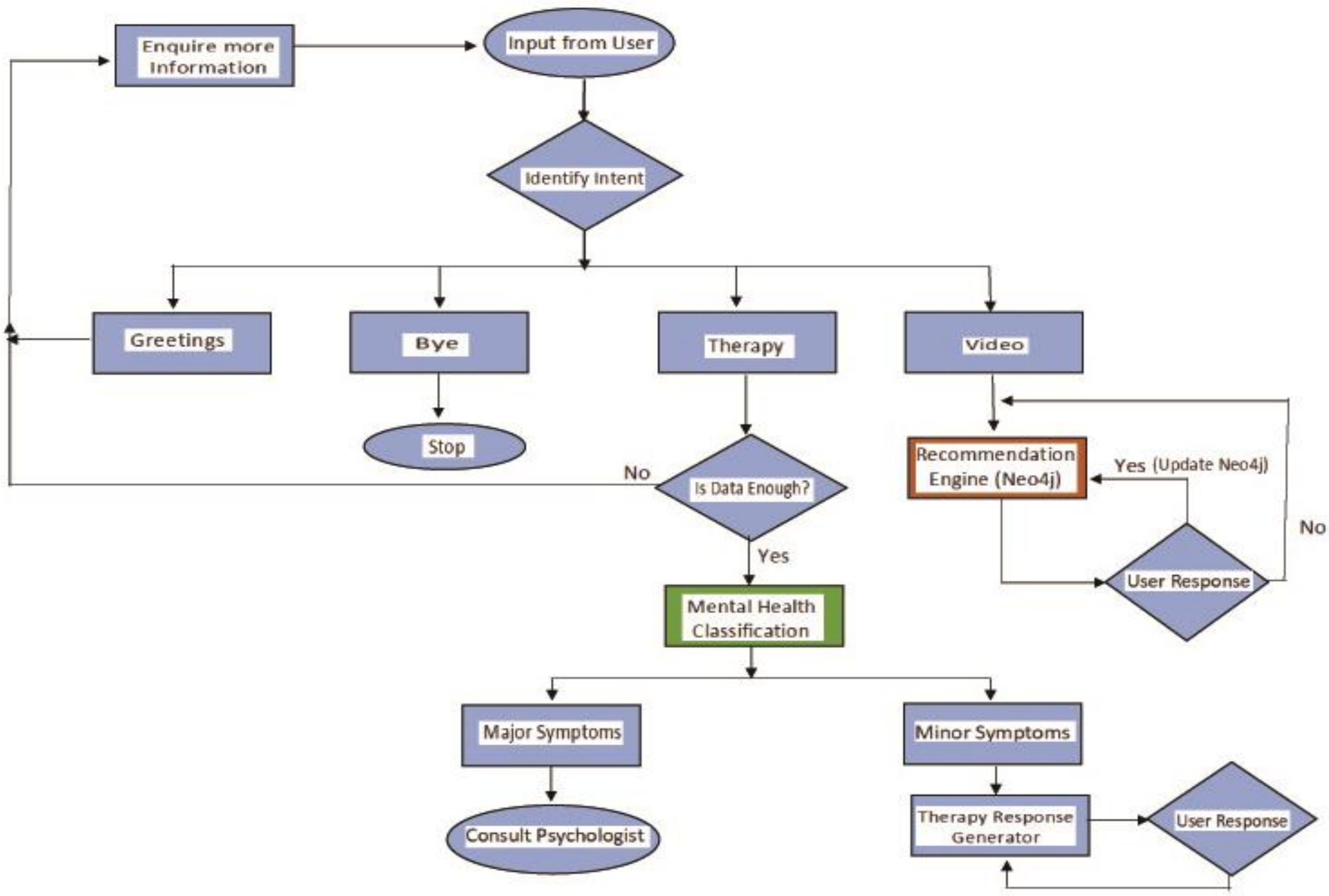

Fig -2:Chatbot Workflow

2) Reddit Dataset

Posts from Reddit are included in this dataset. The data is organised as a CSV file with columns for user responses and the class labelled as “suicidal tendency”.

We also created two datasets from scratch: one for intent recognition model, consisting of user responses and corresponding intents being “greetings'', “therapy”, “video” and “exit”, and the other for user feedback classification model, consisting of user responses and corresponding type of feedback being “positive” or “negative”.

The datasets were pre-processed to remove non-textual characters, links and stop words, followed by the processes of tokenization and vectorization, after which we fed it to the following models for training.

5.2 Intent Recognition

The SVM [6] classifier is utilized for intent recognition. SVM classification calculation is based on finding a partition between hyperplanes characterized by classes of information. Initially the dataset is stacked and vectorized utilizing Term Frequency-Inverse Document Frequency (TF-IDF). The hyperplane for the model is found and at last the client input is classified utilizing preprocessed SVM. The primary aim of SVM is to discover the direct isolating hyperplane which maximizes the margin, i.e., the optimal separating hyperplane (OSH). The set of records accessible for creating classification strategies is separated into two disjoint subsets- a preparing set and a test set. With the help of the SVM classifier, we classify user's input as one of the four classes namely greetings, therapy, video and exit.

5.3: Mental State Classification

We utilise a Bi-LSTM model [7] for multi classification, which receives textual input and predicts the relevant category. Depression, anxiety, addiction, and suicidal ideation are among the anticipated categories.

The LSTM is a type of artificial recurrent neural network that incorporates a memory module that allows it to recall extended sequences. We gathered depression, anxiety, and addiction datasets and pre-processed it by removing punctuations, stop words etc. The tokenizer converts textual input to numeric values. The user's textual input is fed into the Bi-LSTM, which analyses it and predicts the appropriate category. Because Bi-LSTM analyses data in both directions, it is aware of both the past and future context, which increases the accuracy of long-term sequence prediction.

Text vectorization is applied to the input initially. After that, there's an embedding layer that turns each word into a fixed-length vector. The data is then processed in both directions in the bi-directional layer, followed by two dense layers using the activation algorithms ReLU and Softmax, respectively. Finally, we get the predicted label.

5.3 User Feedback Recognition

For every therapy (textual and videos) we provide to the user, the user's feedback is taken as input and is classified into positive or negative. This is done using a Naive Bayes classifier [8]. It is used to determine the likelihood of a class (positive or negative) occurring given the probability of a sentence (user feedback) occurring. That is, for a given user feedback, it predicts it as positive or negative. Bayes theorem for this scenario can be represented as:
P(type/feedback) =P(feedback/type) *P(type)/ P(feedback)
where,
P(type/feedback) is the conditional probability of the type of feedback to be positive/negative, when the user gives a feedback,
P(feedback/type) is the conditional probability of the user feedback given that it should be of type positive/negative,
P(type) is the prior probability of feedback type(positive/negative) obtained from the training data, and
P(feedback) is the probability that a particular feedback is given by the user.
After vectorizing the user feedback using TF-IDF, it is passed into a Naive Bayes classifier to be classified as positive or negative. The classifier was trained to obtain an accuracy of 60%.

6. VIDEO RECOMMENDATION

The three main nodes in the scenario of video recommendation are video node, user node and class node. A video node is a representation of a video with attributes such as the video URL, positive and negative reviews. User node represents a user which has properties like username and password. Class node represents the mental state (which belongs to classes like anxiety, depression and addiction).

The relationships between nodes include "HasClass" arrow from user/video node to a class node, which denotes that a user or a video belongs to a particular class, while "IsPositive" and "IsNegative" arrows from user node to video node denotes the type of feedback user has given to a specific video.

Content-based recommendation works with the data provided for videos. To generate videos, we utilise a cypher query in which we first choose all videos that belong to the same class as the user, and then calculate the ratio of positive to negative ratings for each video. The videos with maximum ratio will be matched by the query and displayed to the user.
Collaborative-based recommendation is provided after a user has given a review (either positive or negative) to the video recommended using content-based recommendation query. Consider the scenario when the current user, say Andy, has given negative review to the content-based recommended video.

In collaborative-based recommendation, we use cypher query to first find all the previous users who had given the same type of review as Andy given to the video provided by content-based recommendation. Then for each such user, we find all the videos to which they had previously given positive review, and display it to Andy, based on user similarity. That is, here we assume that our current user would favourably like the videos that were previously positively reviewed by similar users. This is how we implemented the concept of user similarity using cypher querying.

7. INTEGRATED CHATBOT LOGIC

The individual components include SVM model for intent recognition, LSTM model for mental state recognition, Naïve Bayes models for user feedback for textual therapy and videos and neo4j video recommendation system are combined in the following chatbot logic:
1) The user input is read.
2) Input is passed to the intent recognition model which has four intents, namely greetings, therapy, video and exit.
2.1) If user input (e.g.: “Hello”) is classified as “greetings”, respond the user with salutations like “Hello, how may I assist you?".
2.2) If the user input (e.g.: “I want to stop this therapy session”) is classified as” exit”, the conversation is stopped, and the user is asked to close the chat window.
2.3) If the user input (e.g.:” I want therapy”,” I feel sad and depressed all the time”) is classified as "therapy", the input is further transferred to the LSTM model for mental state recognition.
2.4) If user input (e.g.: “I want to watch some motivational videos”) is classified as "video”, the input is further transferred to the Neo4j system for video recommendation.
3) Once the user input is classified as “therapy”, request more information from the user until it is enough for the LSTM model for classification.
3.1) If the predicted category is major (suicidal tendency), suggest that the user speak with a close friend or family member or consult a psychologist.
3.2) If the predicted category is minor (depression, anxiety, addiction) provide motivating textual therapy.
3.3) Additionally, provide motivational videos using neo4j recommendations.
4)Once the user's input is classified as “video”, use Neo4j for video recommendation.
4.1) Provide the user with videos that have maximum positive to negative review ratio, using content-based recommendation.
4.2) Request for the user's feedback for the provided content-based recommended video. Using this review, provide collaborative-based recommendations, that is display all the videos positively reviewed by similar users.

8.RESULTS

We trained the dataset on six different multi-classification models, out of which the LSTM model demonstrated maximum accuracy of 73%, with long sentences and interdependent class-attributes in the dataset. SVM model showed maximum accuracy for sentences with independent class attributes. For binary classification of user feedback as positive or negative, we prepared a user feedback dataset and trained it on 3 different models of which the Naïve Bayes model showed maximum performance of 82%.

SVM model for intent recognition showed an accuracy of 70% for multi-classification of independent intents. We also implemented video recommendations by creating cypher queries in Neo4j.

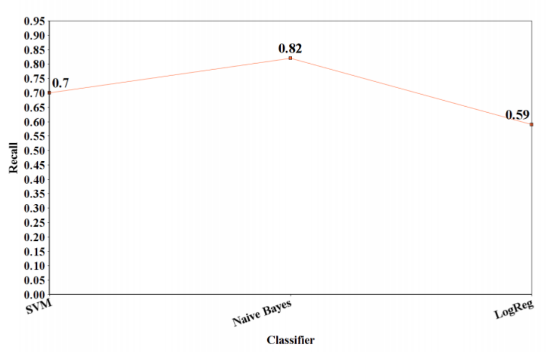

Chart -1: Performance Comparison of Binary Classifier

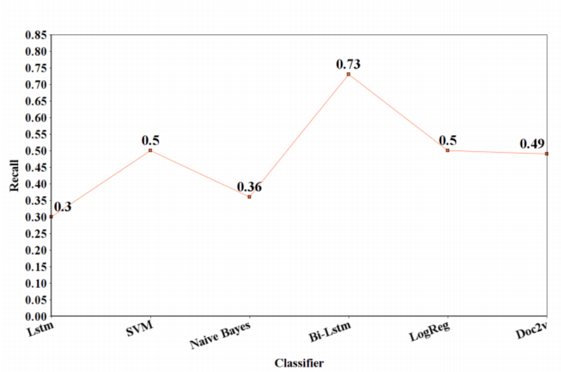

Chart -2: Performance Comparison of Multinomial classifier

9. CONCLUSIONS AND FUTURE WORK

We proposed an intelligent therapeutic chatbot that recognizes mental state from users' reaction, gives literary treatment and suggests motivational recordings depending on their mental state. Dataset collection was a major challenge, since patient-therapist information is private and constrained. Our framework is of great use for users since it disposes of the issue of lack of privacy in attending real-time therapy sessions.

As future work, we could scale the multi-classification model by including more mental states as classes and train the model on the expanded dataset. Better therapy responses are also needed to maximize the user-chatbot experience.

REFERENCES

[1] Kathleen Kara Fitzpatrick, Alison Darcy and Molly Vierhile, "Delivering Cognitive Behavior Therapy to Young Adults with Symptoms of Depression and Anxiety Using a Fully Automated Conversational Agent (Woebot): A Randomized Controlled Trial", JMIR, April 2017

[2] Bayan Abu Shawar & Eric Atwell, "A Comparison Between Alice and Elizabeth Chatbot Systems", University of Leeds, December 2002

[3] Rennie, Jason D. M, and Rifkin, Ryan, "Improving Multiclass Text Classification with the Support Vector Machine" MIT, October 2001

[4] Muhammad Husain Toding Bunga, and Suyanto Suyanto, "Developing a complete Dialogue System using Long Short-Term Memory", IEEE Xplore, March 2020

[5]https://towardsdatascience.com/counsel-chat-bootstrapping-high-quality-therapy-data-971b419f33da

[6]https://monkeylearn.com/text-classification-support-vector-machines-svm/

[7] https://medium.com/analytics-vidhya/building-a-text-classification-model-using-bilstm-c0548ace26f2

[8] Venkatesh, and K. V. Ranjitha, "Classification and Optimization Scheme for Text Data using Machine Learning Naïve Bayes Classifier", IEEE Xplore April 2019