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Research Article

MindIntent: A Chatbot Using SVM for Identifying Mental Health Intervention Intentions

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ABSTRACT

Mental health issues are increasingly acknowledged as vital, yet traditional support systems have limitations in availability, cost, and accessibility. Chatbots provide a scalable solution for real-time support, but their usefulness is dependent on correctly understanding user input. This work uses a Support Vector Machine (SVM) to improve chatbot performance in mental health applications by effectively dealing with high-dimensional data and discriminating between emotional states and intents. We created a chatbot by gathering and annotating text data, preprocessing it, and extracting features with tools like TF-IDF and word embeddings. The SVM model was trained on this data and implemented into the chatbot, allowing for real-time classification of user inputs and contextually relevant responses. Our results show that the SVM-powered chatbot excels at accurately categorizing users.

Keywords: Intention mining, chatbot, mental health, vectorization, support vector machine.

Introduction

Developing a mental health chatbot is necessary for various reasons. For starters, it is available around the clock, allowing customers to receive fast assistance at any time and from any location, including underserved areas. This early intervention capability can track users in real time, giving immediate treatment and potentially avoiding mental health catastrophes. The chatbot is cost-effective, lowering service expenses and allowing for multiple users to be served at once. It assists mental health providers by serving as an additional tool, gathering crucial data, and monitoring patient improvement (1). The chatbot ensures anonymity and privacy, allowing users to share sensitive information while keeping confidentiality. It also functions as an educational resource, providing factual information on mental health, coping skills, and reducing stigma through open dialogue. Natural language processing (NLP) and sentiment analysis are among the key capabilities, as are personalization, crisis management, educational content, and connection with other systems and apps (2). Ethical and privacy problems, ongoing learning, user participation, and collaborations with mental health professionals and technology providers are all important implementation considerations (3). To summarize, a mental health chatbot improves accessibility, provides rapid help, lowers expenses, and supports traditional mental health care, resulting in significantly better mental health outcomes (4).

A Support Vector Machine (SVM) is utilized in a mental health chatbot to categorize user inputs as feelings or intents (5). The SVM determines the best hyperplane that separates classes, such as positive or negative sentiments, or specific intents, such as seeking therapy, after training on labelled text data. The procedure entails preprocessing and feature extraction of text data using techniques such as TF-IDF or word embeddings (6). The trained SVM model then evaluates real-time user communications, categorizing them based on sentiment and intent, allowing the chatbot to provide relevant and supportive responses (7). This enables effective, real-time mental health care and intervention.

Literature Survey

AI-powered chatbots for mental health assistance are being developed across multiple academic corrections, including natural language processing (NLP), machine learning, and mental health informatics. The literature contains a multitude of studies that help us understand the challenges and accomplishments in these fields. Mental health chatbots have gained popularity for their ability to provide accessible, cost-effective, and scalable mental health help. Fitzpatrick et al. [8] investigated the usefulness of conversational agents in delivering cognitive behavioural therapy, finding encouraging results in the treatment of depression and anxiety. Other studies, such as Sweeney et al. [9], have highlighted the significance of chatbots in delivering support outside of traditional clinical settings, giving users rapid access to mental health resources. However, these research highlight limitations, particularly in the precise processing of user input, which is critical for providing suitable replies. SVMs have long been acknowledged as effective in text classification problems due to their capacity to handle high-dimensional input and build decision boundaries that divide classes with the greatest margin. Joachims [10] was among the first to use SVMs for text categorization, demonstrating their superiority to older methods such as Naive Bayes, particularly in jobs with huge feature spaces. Further research, such as that conducted by Vapnik [11], has reinforced SVM's status as a reliable method for binary and multiclass classification issues in NLP, particularly for tasks requiring the identification of sentiment, emotion, and intent in textual data. Feature extraction is an essential step in the creation of effective machine learning models. There has been substantial research into various approaches for converting text into numerical representations that SVM can process. The Term Frequency-Inverse Document Frequency (TF-IDF) method, described in Havrlant [12] , is still widely used due to its simplicity and efficacy in emphasizing the relevance of terms within a document corpus. More recent studies, such as Mikolov et al. [13], used word embeddings (e.g., Word2Vec) as a more sophisticated method of capturing semantic links between words, resulting in better performance in text categorization tasks. These strategies are essential for preparing data for SVM training in chatbot development. The incorporation of machine learning models into chatbot systems is a well-studied topic in AI research. Hussain et al. [14] and Zhang et al. [15] explored the use of dialogue systems in a variety of applications, highlighting the significance of real-time processing and user feedback loops in improving chatbot responses. Furthermore, works such as Jannach et al. [16] have investigated the architecture of end-to-end conversational models that incorporate text categorization components to improve contextual understanding of user input. These studies highlight the need of seamless integration in ensuring the performance and dependability of AI-powered chatbots in real-world scenarios. User input is critical in determining the efficacy of mental health chatbots. William J. Bingley et al. [17] emphasize the need of user-centered design in developing AI tools for mental health, stating that user happiness and trust are important to the effectiveness of such therapies. Positive feedback in this research is frequently associated with the chatbot's capacity to effectively grasp and respond to user requests, highlighting the value of strong NLP approaches, such as SVM-based categorization, in improving user experience. The literature suggests that SVMs are an excellent tool for text categorization in mental health chatbots, especially when combined with good feature extraction techniques and incorporated into well-designed systems. The constant challenge is to increase the accuracy and relevance of chatbot responses while maintaining the high standards required for effective mental health support. This study expands on previous research by applying SVMs to the unique context of mental health, adding to the emerging field of AI-driven mental health intentions.

Dataset

The dataset in JSON format is downloaded from Kaggle [18] which is collection of dialogues that includes guidance for those with anxiety and depression, conversations about classical therapy, mental health FAQs and basic chats. The dataset can be used to train a chatbot model which acts like a therapist and offers emotional support to those who are depressed and anxious. There are intentions in the dataset. A user's message's "intent" refers to their purpose. For instance, the intent would be sad if the user tells the chatbot “I am sad.” There are some Patterns and Responses that are appropriate for a certain aim, depending on what it is. Patterns are instances of user messages that correspond with the intent, and Responses are the responses the chatbot gives that match the intent. To help the model detect a certain purpose, a variety of intents are defined, and their patterns and responses are used as training data.

Methodology

The json module of python is imported which is used to parse the JSON data. Machines can quickly analyze and generate JSON (JavaScript Object Notation). The method load_intents_from_json(filepath) is defined here. It is responsible for loading JSON data from files. The path to the JSON file containing the intents and replies is expected to be provided by the argument filepath [19].

The raw unstructured data from the JSON file is arranged into structured format that is ready for further analysis for training the machine learning model. Initially dictionary is created to map the intent tag to potential answers and lists to store user input patterns and the intent tags that correspond with them. Each intent is iterated through in the JSON data, populating lists and dictionaries with patterns, tags, and responses. Patterns and tag lists are converted into dataframes for easier data handling and visualization.

CountVectorizer

1. Tokenization:

The initial stage of CountVectorizer is the breakdown of text into individual tokens (usually words) [20]. For example, consider the following sentence: "Hello there" is broken in tokens as ["Hello", "there"]

2. Vocabulary Building:

The CountVectorizer then creates a vocabulary using these tokens. The vocabulary is simply a mapping from each unique token to an index [21,22]. For example, imagine you had the following text patterns:"Hello there" ,"Hi there", "Hello again". The vocabulary may be "Hello":0."There":1."Hi":2"Again":3.

3. Term Frequency (TF)

Term frequency (TF) relates to how often a term seems in a document. It can be planned as follows:

$$TF(t,d) = \frac{Number\ of\ times\ the\ term\ t\ appears\ in\ d}{Total\ number\ of\ terms\ in\ d} \quad (1)$$

The CountVectorizer calculates term frequency for each document (text pattern). Term frequency discusses to how many numbers of periods each term (word) seems in the document (12). For instance, consider the pattern "Hello there": The frequency vector is as follows: "Hello": 1, "there": 1, "Hi": 0, and "again": 0.

4. Creating Document term-matrix:

The document-term matrix (DTM) is a sparse matrix with rows representing documents and columns representing vocabulary terms. The values in the matrix denote term frequency [23].

For example, with the given language and text patterns, the DTM could look like: [1, 1, 0, 0], # "Hello there" [0, 1, 1, 0], # "Hi there" [1, 0, 0, 1] # "Hello again"

The Document-Term Matrix (DTM) is a matrix where each element X_{ij} represents the term frequency of term j in document I [24]. Mathematically: Let D represent the number of papers.

Let V be the number of distinct terms in the lexicon.

The DTM X is D×V matrix containing:

$$X_{ij} = TF(t_j, d_i) \quad (2)$$

X_{ij} is the count of term j in document i, t_j is the j-th term in vocabulary, and d_i is the i^{th} document.

If we consider simple example

Documents:

i. "Hello there"
ii. "Hi there"
iii. "Hello again"

Vocabulary:
"Hello" corresponds to Index 0, "there" to Index 1, "Hi" to Index 2, and "again" to Index 3.

The term document matrix is given as in table 1

Table 1. Term document matrix.

Document	Hello	There	Hi	again
i	1	1	0	0
ii	0	1	1	0
iii	1	0	0	1

5. TF-IDF (Term frequency -inverse document frequency)

While CountVectorizer does not explicitly compute TF-IDF, a similar notion is frequently employed in text processing. The TF-IDF is computed as follows:

$$TF - IDF(t, d) = TF(t, d) \times IDF(t) \quad (3)$$

IDF is computed as follows

$$IDF(t) = log\left(\frac{N}{1+DF(t)}\right) \quad (4)$$

Where N is the overall numeral of documents, and DF(t) is the numeral of documents that include the phrase t.TF-IDF is advanced measure that modifies word frequency based on the term's relevance across documents [25].

These mathematical ideas are the foundation of text vectorization approaches, which convert textual data into numerical features that may be employed in machine learning models.

Label Encoder

The LabelEncoder looks at all unique labels in df['tags']. For example, if df['tags'] includes ["greeting", "farewell", "greeting"], the LabelEncoder will identify two distinct labels: "greeting" and "farewell". It then allocates an integer to each unique label, like "greeting" → 0 or "farewell" → 1. It translates each label in the df['tags'] Series to the associated number. So, if the original labels are ["greeting", "farewell", "greeting"], the changed labels are [0, 1, 0] [26].

It results in an array of integers representing the labels, which is suited for usage in machine learning models. By encoding labels categorical data is prepared for Input numerical characteristics into algorithms that require them, which will help you train and evaluate your machine learning model.

Training the Support Vector machine model with linear kernel

To evaluate model performance, the dataset is separated into two parts: training and testing. This ensures that the model is trained on one segment of the data before being tested on a previously unseen portion.

Model initialization creates a Support Vector Machine classifier with a linear kernel. The model fits to the training data and learns to differentiate classes based on the attributes provided [27].

A linear SVM's decision boundary (hyperplane) that separates the data is a linear function:

$$w \cdot x + b = 0 \quad (5)$$

Where w represents the weight vector that affects the hyperplane's orientation. x represents the instance's feature vector. b represents the bias term that pushes the hyperplane away from the origin.

The aim is to discover the hyperplane that capitalize on the margin, which is the distance amongst the hyperplane and the nearby data points in each class.

The Margin is given by

$$Margin = \frac{2}{\|w\|} \quad (6)$$

To maximize the margin, following optimization problem should be solved. The objective function is to minimize the norm of w.

$$Minimize = \frac{1}{2}\|w\|^2 \quad (7)$$

The constraint is to ensure that all data points are accurately classified using the margin:

$$y_i(w \cdot x_i + b) \geq 1 \quad (8)$$

Where, y_i is the label of i^{th} training sample (+1 or -1) and x_i is the feature vector of the i^{th} training sample [28,29].

Solving the fundamental issue directly might be computationally expensive, especially for large feature sets. Instead, we address the dual problem, which is frequently more manageable [30]:

The dual objective function is

$$Maximize \ \sum_{i-1}^{N} \propto_i - \frac{1}{2}\sum_{i-1}^{N}\sum_{j-1}^{N} \propto_i \propto_j \ y_i y_j (x_i \cdot x_j) \quad (9)$$

Subjected to constraint

$$\sum_{i-1}^{N} \propto_i \ y_i = 0 \ \ where \ \propto_i \geq 0 \ is \ Lagrange \ multiplier \quad (10)$$

The dual problem is a quadratic programming problem that optimizes α_i under given constraints [31]. Once the optimization problem has been addressed, the decision function used to classify additional data points.

$$f(x) = sign(\sum_{i-1}^{N} \propto_i \ y_i (x_i \cdot x) + b) \quad (11)$$

Where, α_i are the Lagrange multipliers obtained from dual problem. x_i are the support vectors.b is the bias term.

The linear SVM solves an optimization issue to regulate the ideal hyperplane that capitalize on class separation [32]. The dual formulation is a computationally efficient technique to approach this problem, particularly in high-dimensional spaces.

Results and discussion

Predict intent based on user input.

The function gets the user's input text. Using the fitted CountVectorizer, converts the user's supplied text into numerical format. Uses the trained SVM model to predict the user input's encoded label. The fitting LabelEncoder converts the encoded label back to the original purpose string. And, it returns the projected intent.

Let's look at an example to make things clearer: Suppose the user enters "Hello". The CountVectorizer converts "Hello" into a sparse matrix using the vocabulary gained from the training data. The SVM model predicts the label index from the converted input. The LabelEncoder translates the projected label index to the original intent label, such as “greeting". The function returns "greeting" as the expected intent.

Get a response based on projected purpose.

The user provides input. Intent is predicted based on the input. The predicted intent is used to generate a list of probable answers. The first response in the list is printed. The get_response function enables the chatbot to dynamically generate appropriate responses based on the user's input and expected intent.

For example, The user types "Hi".The predict_intent function predicts that the intent is "greeting".The get_response function is invoked with the purpose "greeting".The function gets the list of responses for the "greeting" intent from the responses dictionary. The function returns the list ["Hello there!", "Hi, how may I aid you?", and "Hey! "How are you?"]

The user interaction cycle continues until "goodbye" is entered.

In the output it continuously asks the user for input. Reads and processes user inputs. To terminate the loop, this function checks if the user input is "goodbye". Uses the trained model to estimate the user input's intent. Returns a response depending on projected purpose. Displays the projected intent and reaction to the user.

The conversation is shown in figure 1

```
Enter your message:  hi
Predicted Intent: greeting
Response: Hello there. Tell me how are you feeling today?
Enter your message:  how are you?
Predicted Intent: about
Response: I'm Pandora, your Personal Therapeutic AI Assistant. How are you feeling today
Enter your message:  I am lonely
Predicted Intent: sad
Response: I'm sorry to hear that. I'm here for you. Talking about it might help. So, tell me why do you think you're feeling this way?
Enter your message:  I don't want to talk about it
Predicted Intent: not-talking
Response: Talking about something really helps. If you're not ready to open up then that's ok. Just know that i'm here for you, whenever you need me.
Enter your message:  I'm scared
Predicted Intent: scared
Response: It's only natural to feel this way. I'm here for you.
Enter your message:  Tell me a joke
Predicted Intent: jokes
Response: mental health is not a joke.
Enter your message:  Tell me a fact about mental health
Predicted Intent: mental-health-fact
Response: According to a UNICEF report, One in seven Indians between 15-24 years of age feels depressed
Enter your message:  What's the difference between sadness and depression?
Predicted Intent: fact-32
Response: Sadness is a normal reaction to a loss, disappointment, problems, or other difficult situations. Feeling sad from time to time is just another part of being
human. In these cases, feelings of sadness go away quickly and you can go about your daily life. Other ways to talk about sadness might be feeling low, feeling down, o
r feeling blue.A person may say they are feeling depressed, but if it goes away on its own and doesn't impact life in a big way, it probably isn't the illness of depre
ssion. Depression is a mental illness that affects your mood, the way you understand yourself, and the way you understand and relate to things around you. It can also
go by different names, such as clinical depression, major depressive disorder, or major depression. Depression can come up for no reason, and it lasts for a long time.
It's much more than sadness or low mood. People who experience depression may feel worthless or hopeless. They may feel unreasonable guilty. Some people may experience
depression as anger or irritability. It may be hard to concentrate or make decisions. Most people lose interest in things that they used to enjoy and may isolate thems
elves from others. There are also physical signs of depression, such as problems with sleep, appetite and energy and unexplainable aches or pains. Some may experience
difficult thoughts about death or ending their life (suicide). Depression lasts longer than two weeks, doesn't usually go away on its own, and impacts your life. It's
a real illness, and it is very treatable. It's important to seek help if you're concerned about depression.
Enter your message:  goodbye
Goodbye! Have a great day!
```

Fig. 1 Chatbot conversation

The distribution of patterns of intent is shown in figure 1

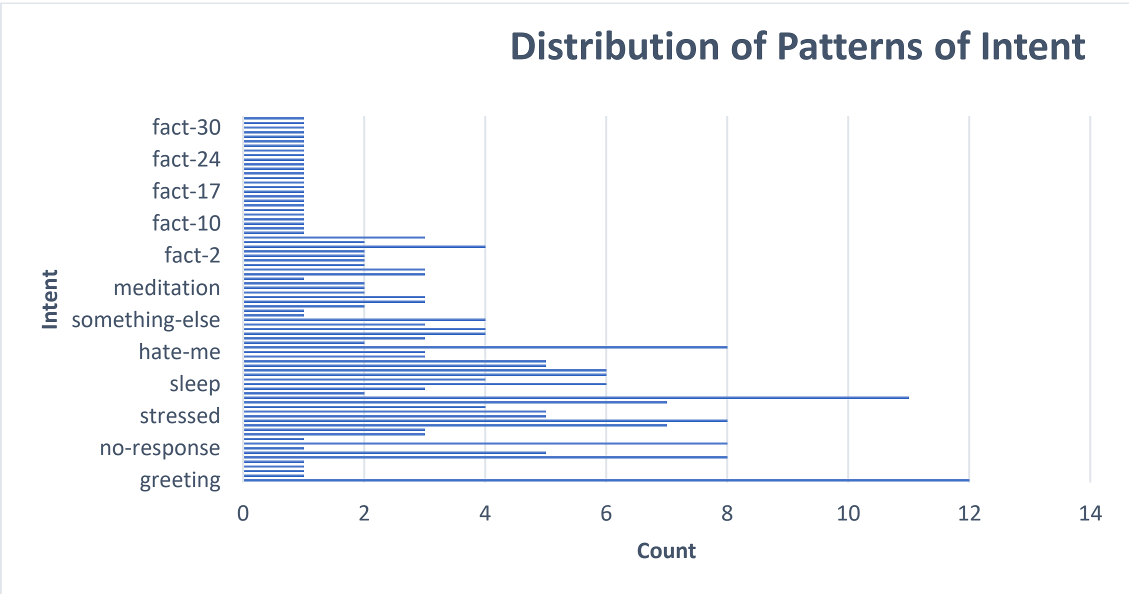

Fig. 2 Distribution of patterns of Intent

Conclusion and Future Work

Adopting a Support Vector Machine (SVM) for a mental health chatbot improves its capacity to effectively monitor and identify user attitudes and intents. The chatbot can provide personalized, helpful responses in real time by taking advantage of SVM's ability to detect the ideal boundaries between different emotional states and intentions. This technique not only allows for early detection of mental health disorders, but it also enables timely and suitable solutions. Integrating SVM into the chatbot offers effective, scalable, and accessible mental health support, resulting in increased user well-being and more efficient mental health treatment.

The existing chatbot is a decent start, but it requires various enhancements. Future developments will involve increasing the intent dataset, upgrading to advanced models such as BERT or GPT, and including context management for cohesive talks. Adding multi-turn chat features, sentiment analysis, and support for many languages would improve the user experience. Personalization, voice integration, dynamic responses, and robust error handling are all important areas for development. Additionally, integrating with external systems, incorporating user feedback loops, and addressing ethical concerns would improve the chatbot's usefulness and versatility.

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