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# Building Your Own Chatbot: Exploring Natural Language Processing Techniques With Nltk And Nerual Networks

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**ABSTRACT**
Mental health issues, such as anxiety, depression, and other psychological disturbances, have become a significant public health concern globally. Identifying individuals at risk of these conditions early on can lead to timely interventions and improved outcomes. With the rise of technology and the increasing use of smartphones and wearable devices, there is an opportunity to develop an innovative system that can monitor emotional health in real-time, helping to detect potential psychological disturbances before they escalate. Traditionally, mental health assessments relied on self-reporting and periodic check-ins with mental health professionals. These approaches often had limitations, as individuals may not always accurately report their emotional state, and there could be significant delays between assessments. Additionally, access to mental health services was not always readily available, leading to potential delays in diagnosis and treatment. Therefore, the need for an innovative system for monitoring emotional health arises from the desire to overcome the limitations of traditional approaches. By leveraging technology, such as machine learning, natural language processing, we can create a continuous and unobtrusive monitoring system. Such a system could gather real-time data on an individual's emotional state, behavior, and physiological responses. Early detection of emotional disturbances can lead to timely intervention and support, improving the overall mental well-being of individuals and reducing the burden on mental health services. This innovative monitoring system has the potential to significantly improve mental health outcomes on a broader scale. It offers a proactive approach to emotional well-being, empowering individuals to take control of their mental health and providing an invaluable tool for mental health professionals in identifying and supporting those at risk of psychological disturbances.

**Keywords:** Chatbot Development, Natural Language Processing (NLP), NLTK (Natural Language Toolkit), Real-Time Monitoring, Text Classification.



## 1. INTRODUCTION

Mental illness is a health problem that undoubtedly impacts emotions, reasoning, and social interaction of a person. These issues have shown that mental illness gives serious consequences across societies and demands new strategies for prevention and intervention. To accomplish these strategies, early detection of mental health is an essential procedure. Medical predictive analytics will reform the healthcare field broadly as discussed by Miner et al. [1]. Mental illness is usually diagnosed based on the individual self-report that requires questionnaires designed for the detection of the specific patterns of feeling or social interactions [2]. With proper care and treatment, many individuals will hopefully be able to recover from mental illness or emotional disorder [3]. Machine learning is a technique that aims to construct systems that can improve through experience by using advanced statistical and probabilistic techniques. It is believed to be a significantly useful tool to help in predicting mental health. It is allowing many researchers to acquire important information from the data, provide personalized experiences, and develop automated intelligent systems [4]. The widely used algorithms in the field of machine learning such as support vector machine, random forest, and artificial neural networks have been utilized to forecast and categorize the future events [5].

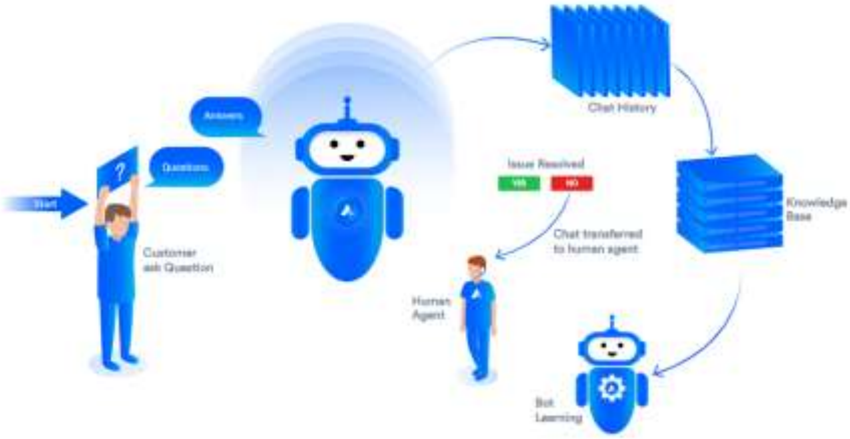


Fig. 1: Developing Chatbots with NLP in AI & ML.

Supervised learning in machine learning is the most widely applied approach in many types of research, studies, and experiments, especially in predicting illness in the medical field. In supervised learning, the terms, attributes, and values should be reflected in all data instances [6]. More precisely, supervised learning is a classification technique using structured training data [7]. Meanwhile, unsupervised learning does not need supervision to predict. The main goal of unsupervised learning is handling data without supervision. It is very limited for the researchers to apply unsupervised learning methods in the clinical field.The World Health Organization (WHOTh reports the region-wise status of different barriers in diagnosing mental health problems and encourages researchers to be equipped with the scientific knowledge to address the issue of mental health [9]. Now, there are various techniques to predict the state of mental health due to advancement of technology. Research in the field of mental health has increased recently and contributed to the information and publications about different features of mental health, which can be applied in a wide range of problems [10]. Many steps are involved in diagnosing mental health problems, and it is not a straightforward process that can be done quickly. Generally, the diagnosis will begin with a specific interview that is filled with questions about symptoms, medical history, and physical examination. Besides that, psychological tests and assessment tools are also available and are used to diagnose a person for mental health problems. There are several types of research carried out to investigate and examine the movements of the face to identify certain mental disorders [11]. The increase of research in the mental health field has led to the rise of information in the form of finding suitable solutions to reduce mental health problems. However, the precise reasons for mental illnesses are still unclear and uncertain.

## 2. LITERATURE SURVEY

According to the paper by Greenstein et al., classification of childhood-onset schizophrenia has been performed [12]. The data consist of genetic information, clinical information, and brain magnetic resonance imaging. The authors use a random forest method to calculate the probability of mental disorder. Random forest is being used in this paper because it has lower error rates compared with other methods. The accuracy of 73.7% is obtained after the classification.In one of the research works conducted by Jo et al., they used network analysis and machine learning approaches to identify 48 schizophrenia patients and 24 healthy controls [13]. The network properties were rebuilt using the probabilistic brain tractography. After that, machine learning is being applied to label schizophrenia patients and health controls. Based on the result, the highest accuracy is achieved by the random forest model with an accuracy of 68.6% followed by the multinomial naive Bayes with an accuracy of 66.9%. Then, the XGBoost accuracy score is 66.3% and the support vector machine shows an accuracy of 58.2%. Most of the machine learning algorithms show promising levels of performance in predicting schizophrenia patients and healthy controls. The support vector machine, which is a machine learning model, has been implemented to classify schizophrenia patients [14]. The data set is obtained from the 20 schizophrenia patients and 20 healthy controls. Then, the support vector machine algorithm is used for classification with the help of functional magnetic resonance imaging and single nucleotide polymorphism. After the classification, an accuracy of 0.82 is achieved with the functional magnetic resonance imaging. For the single nucleotide polymorphism, an accuracy of 74% is obtained. Srinivasagopalan et al. [15] used a deep learning model to diagnose schizophrenia. The National Institute of Health provides the data set for the experiments. The accuracy of each machine learning algorithm is obtained and recorded. The results obtained from the experiment show that deep learning showed the highest accuracy with 94.44%. The random forest recorded an accuracy of 83.33% followed by logistic regression with an accuracy of 82.77%. Then, the support vector machine showed an accuracy of 82.68% in this experiment.

In another study conducted by Pla¨schke et al., the schizophrenia patients were distinguished from the matched health controls based on the resting-state functional connectivity [16]. Resting-state functional connectivity could be used as a spot of functional dysregulation in specific networks that are affected in schizophrenia. The authors have used support vector machine classification and achieved 68% accuracy. Pinaya et al. applied the deep belief network to interpret features from neuromorphometry data that consist of 83 healthy controls and 143 schizophrenia patients [17]. The model can achieve an accuracy of 73.6%; meanwhile, the support vector machine obtains an accuracy of 68.1%. The model can detect the massive difference between classes involving cerebrum components. In 2018, Pinaya et al. proposed a practical approach to examine the brain-based disorders that do not require a variety of cases [18]. The authors used a deep autoencoder and can produce different values and patterns of neuroanatomical deviations.A machine learning algorithm is developed to predict the clinical remission from a 12-week course of citalopram [19]. Data are collected from the 1949 patients that experience depression of level 1. A total of 25 variables from the data set are selected to make a better prediction outcome. Then, the gradient boosting method is being deployed for the prediction because of its characteristics that combine the weak predictive models when built. An accuracy of 64.6% is obtained by using the gradient boosting method. In order to identify depression and anxiety at an early age, a model has been proposed by Ahmed et al. [20]. The model involves psychological testing, and machine learning algorithms such as convolutional neural network, support vector machine, linear discriminant analysis, and K-nearest neighbour have been used to classify the intensity level of the anxiety and depression, which consists of two data sets. Based on the results obtained, the convolutional neural network achieved the highest accuracy of 96% for anxiety and 96.8% for depression. The support vector machine showed a great result and was able to obtain an accuracy of 95% for anxiety and 95.8% for depression. Besides that, the linear discriminant analysis reached the accuracy of 93% for anxiety and 87.9% for depression. Meanwhile, the K-nearest neighbour obtained the lowest accuracy among the models with 70.96% for anxiety and 81.82% for depression. Hence the convolutional neural network can be a helpful model to assist psychologists and counsellors for making the treatments efficient.

## 3. PROPOSED METHODOLOGY

An "Innovative System for Monitoring Emotional Health to Identify Individuals at Risk of Psychological Disturbances" is a conceptual framework or technological solution designed to address the critical issue of mental health monitoring and early identification of individuals who may be at risk of psychological disturbances. The primary objective of this innovative system is to proactively monitor the emotional well-being of individuals and identify signs or patterns that suggest they may be at risk of psychological disturbances or mental health issues. It aims to provide timely support and intervention to those in need.

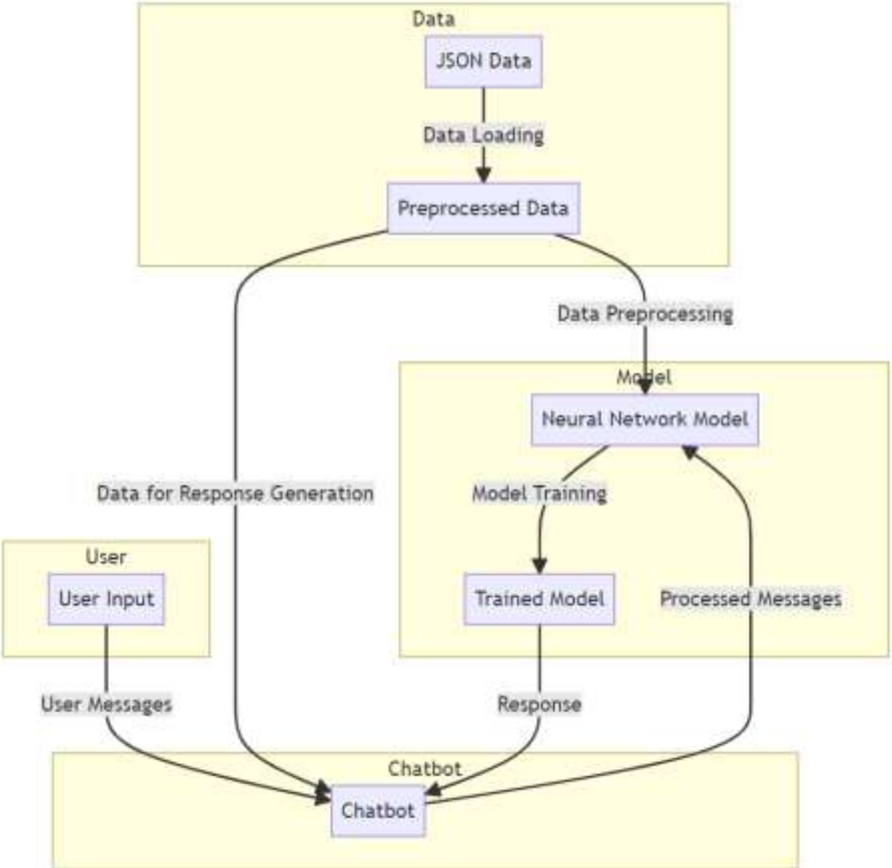


Fig. 2: Overall design of proposed system.

Recurrent Neural Networks (RNNs) are a type of deep neural network particularly suited for processing sequential data due to their memory capabilities, which allow them to retain information from previous inputs. Unlike convolutional neural networks (CNNs), which excel in spatial data like images, RNNs are ideal for tasks involving time dependencies such as speech recognition, machine translation, text generation, sentiment analysis, and behavior recognition. The RNN architecture typically includes an input layer, a hidden layer with cyclical connections to maintain temporal memory, and an output layer. In this study, RNNs processed 10 normalized input features—age, BMI, marital status, education level, family income, alcohol use, smoking, heat exposure, noise, and shift work—to predict lipid health status (1 for normal, 0 for abnormal). Forward propagation involves computing hidden states at each time step using weight matrices (W, U, V) and activation functions like tanh or ReLU, with SoftMax at the output. These weights are shared across time steps. For training, the Backpropagation Through Time (BPTT) algorithm is used to update weights by propagating error gradients from the output back through each time step. This enables the network to learn dependencies over time, improving prediction accuracy in time-series health data analysis.

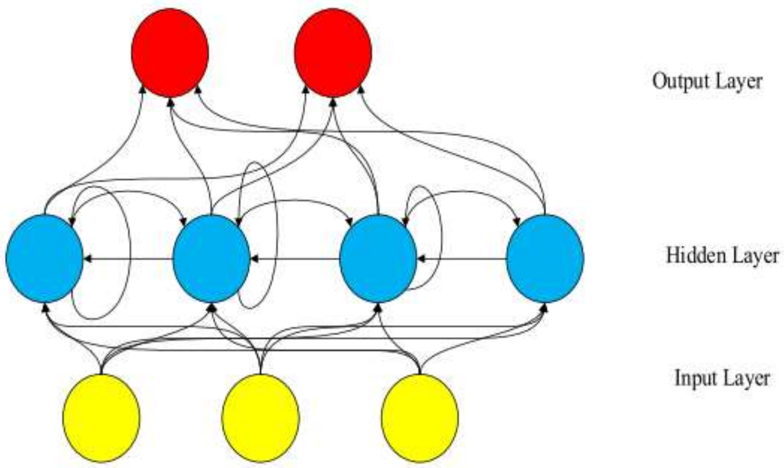


Fig. 3: RNN structure overview.

As can be seen from the figure above, the RNN structure is relatively simple. It mainly consists of an Input Layer, a Hidden Layer, an Output Layer, and an arrow in the Hidden Layer represents the cyclic update of data, which is the method to realize the time memory function. The input levels of this paper were: age, BMI, marital status, education level, family income, alcohol consumption, smoking, exposure to high temperature, noise, shift work. The 10-dimensional data were normalized and input into the RNN model. After the extraction of hidden layer depth features, the output layer output the sequence of lipid health status, in which 1 represented normal lipid status and 0 represented abnormal lipid status.

## 4. RESULTS AND DISCUSSION

Figure 4(a) displays a portion of the original dataset used for training the chatbot. It shows examples of intents or patterns along with their corresponding tags and responses. Figure 4(b) shows how the original dataset has been structured after converting it into a panda DataFrame. It focuses on the 'patterns' and 'tags' columns. The 'patterns' column contains the input text or user queries. The 'tags' column contains labels or categories associated with the input patterns.

| | tag | patterns | responses |
|---|---|---|---|
| 0 | greeting | [Hi, Hey, Is anyone there?, Hi there, Hello, H... | [Hello there. Tell me how are you feeling toda... |
| 1 | morning | [Good morning] | [Good morning. I hope you had a good night's s... |
| 2 | afternoon | [Good afternoon] | [Good afternoon. How is your day going?] |
| 3 | evening | [Good evening] | [Good evening. How has your day been?] |
| 4 | night | [Good night] | [Good night. Get some proper sleep, Good night... |
| ... | ... | ... | ... |
| 75 | fact-28 | [What do I do if I'm worried about my mental h... | [The most important thing is to talk to someon... |
| 76 | fact-29 | [How do I know if I'm unwell?] | [If your beliefs , thoughts , feelings or beha... |
| 77 | fact-30 | [How can I maintain social connections? What i... | [A lot of people are alone right now, but we d... |
| 78 | fact-31 | [What's the difference between anxiety and str... | [Stress and anxiety are often used interchange... |
| 79 | fact-32 | [What's the difference between sadness and dep... | [Sadness is a normal reaction to a loss, disap... |

80 rows × 3 columns

(a)

| | tag | patterns | responses |
|---|---|---|---|
| 0 | greeting | Hi | [Hello there. Tell me how are you feeling toda... |
| 1 | greeting | Hey | [Hello there. Tell me how are you feeling toda... |
| 2 | greeting | Is anyone there? | [Hello there. Tell me how are you feeling toda... |
| 3 | greeting | Hi there | [Hello there. Tell me how are you feeling toda... |
| 4 | greeting | Hello | [Hello there. Tell me how are you feeling toda... |
| ... | ... | ... | ... |
| 227 | fact-29 | How do I know if I'm unwell? | [If your beliefs , thoughts , feelings or beha... |
| 228 | fact-30 | How can I maintain social connections? What if... | [A lot of people are alone right now, but we d... |
| 229 | fact-31 | What's the difference between anxiety and stress? | [Stress and anxiety are often used interchange... |
| 230 | fact-32 | What's the difference between sadness and depr... | [Sadness is a normal reaction to a loss, disap... |
| 231 | fact-32 | difference between sadness and depression | [Sadness is a normal reaction to a loss, disap... |

232 rows × 3 columns

(b)

Figure 4: Display of the sample dataset. (a) original dataset. (b) dataset after converting into a data frame with patterns and tags.

Figure 5 displays a summary of the unique values found in the 'tag' column of the DataFrame. It shows the different categories or tags that the chatbot has been trained to recognize. It provides an overview of the classes or intents that the chatbot can identify.

```
array(['greeting', 'morning', 'afternoon', 'evening', 'night', 'goodbye',
       'thanks', 'no-response', 'neutral-response', 'about', 'skill',
       'creation', 'name', 'help', 'sad', 'stressed', 'worthless',
       'depressed', 'happy', 'casual', 'anxious', 'not-talking', 'sleep',
       'scared', 'death', 'understand', 'done', 'suicide', 'hate-you',
       'hate-me', 'default', 'jokes', 'repeat', 'wrong', 'stupid',
       'location', 'something-else', 'friends', 'ask', 'problem',
       'no-approach', 'learn-more', 'user-agree', 'meditation',
       'user-meditation', 'pandora-useful', 'user-advice',
       'learn-mental-health', 'mental-health-fact', 'fact-1', 'fact-2',
       'fact-3', 'fact-5', 'fact-6', 'fact-7', 'fact-8', 'fact-9',
       'fact-10', 'fact-11', 'fact-12', 'fact-13', 'fact-14', 'fact-15',
       'fact-16', 'fact-17', 'fact-18', 'fact-19', 'fact-20', 'fact-21',
       'fact-22', 'fact-23', 'fact-24', 'fact-25', 'fact-26', 'fact-27',
       'fact-28', 'fact-29', 'fact-30', 'fact-31', 'fact-32'],
      dtype=object)
```

Figure 5: Presents the unique values of column tag.

Figure 6 is a representation of the architecture of the LSTM (Long Short-Term Memory) model used in the chatbot. It shows a detailed summary of the model's layers, including input dimensions, layer types (e.g., embedding, LSTM), the number of units or neurons in each layer, activation functions, and the total number of trainable parameters.

```
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        (None, 18, 100)           30400
_________________________________________________________________
lstm (LSTM)                  (None, 18, 32)            17024
_________________________________________________________________
layer_normalization (LayerNo (None, 18, 32)            64
_________________________________________________________________
lstm_1 (LSTM)                (None, 18, 32)            8320
_________________________________________________________________
layer_normalization_1 (Layer (None, 18, 32)            64
_________________________________________________________________
lstm_2 (LSTM)                (None, 32)                8320
_________________________________________________________________
layer_normalization_2 (Layer (None, 32)                64
_________________________________________________________________
dense (Dense)                (None, 128)               4224
_________________________________________________________________
layer_normalization_3 (Layer (None, 128)               256
_________________________________________________________________
dropout (Dropout)            (None, 128)               0
_________________________________________________________________
dense_1 (Dense)              (None, 128)               16512
_________________________________________________________________
layer_normalization_4 (Layer (None, 128)               256
_________________________________________________________________
dropout_1 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_2 (Dense)              (None, 80)                10320
=================================================================
Total params: 95,824
Trainable params: 95,824
Non-trainable params: 0
```

Figure 6: Model summary of LSTM.

```
Epoch 1/50
230/232 [============================>.] - ETA: 0s - loss: 4.8166 - acc: 0.0174WARNING:ten:
on metric `accuracy` which is not available. Available metrics are: loss,acc
232/232 [==============================] - 4s 17ms/sample - loss: 4.8240 - acc: 0.0172
Epoch 2/50
230/232 [============================>.] - ETA: 0s - loss: 3.7604 - acc: 0.1000WARNING:ten:
on metric `accuracy` which is not available. Available metrics are: loss,acc
232/232 [==============================] - 1s 4ms/sample - loss: 3.7663 - acc: 0.0991
Epoch 3/50
230/232 [============================>.] - ETA: 0s - loss: 3.0389 - acc: 0.2609WARNING:ten:
on metric `accuracy` which is not available. Available metrics are: loss,acc
232/232 [==============================] - 1s 4ms/sample - loss: 3.0493 - acc: 0.2586
Epoch 4/50
220/232 [===========================>..] - ETA: 0s - loss: 2.5307 - acc: 0.4182WARNING:ten:
on metric `accuracy` which is not available. Available metrics are: loss,acc
232/232 [==============================] - 1s 4ms/sample - loss: 2.5476 - acc: 0.4095
```

```
230/232 [============================>.] - ETA: 0s - loss: 0.0278 - acc: 0.9957WARNING:tens
on metric `accuracy` which is not available. Available metrics are: loss,acc
232/232 [==============================] - 1s 5ms/sample - loss: 0.0276 - acc: 0.9957
Epoch 47/50
230/232 [============================>.] - ETA: 0s - loss: 0.0271 - acc: 0.9957WARNING:tens
on metric `accuracy` which is not available. Available metrics are: loss,acc
232/232 [==============================] - 1s 5ms/sample - loss: 0.0270 - acc: 0.9957
Epoch 48/50
230/232 [============================>.] - ETA: 0s - loss: 0.0612 - acc: 0.9913WARNING:tens
on metric `accuracy` which is not available. Available metrics are: loss,acc
232/232 [==============================] - 1s 6ms/sample - loss: 0.0609 - acc: 0.9914
Epoch 49/50
230/232 [============================>.] - ETA: 0s - loss: 0.0394 - acc: 0.9957WARNING:tens
on metric `accuracy` which is not available. Available metrics are: loss,acc
232/232 [==============================] - 1s 5ms/sample - loss: 0.0392 - acc: 0.9957
Epoch 50/50
230/232 [============================>.] - ETA: 0s - loss: 0.0349 - acc: 0.9957WARNING:tens
on metric `accuracy` which is not available. Available metrics are: loss,acc
232/232 [==============================] - 1s 5ms/sample - loss: 0.0349 - acc: 0.9957
```

Figure 7: Training performance of LSTM model with accuracy, and loss for 232 epochs.

```
you: Hi! How are you?
model: Hi there. How are you feeling today?
```

```
you: Maybe I just didn't want to be born :)
model: I want to help you. I really do. But in order for me to help you, you're gonna have to talk to me.
```

```
you: help me:
model: Tell me your problem so that i can assist you
```

```
you: :
model: Not sure I understand that.
```

```
Chatbot: Hi! I'm your friendly chatbot. How can I assist you today?
You: 'hi'
you: 'hi'
model: Sorry, I didn't understand you.
```

Figure 8: Sample predicted conversation between patient and proposed model for monitoring emotional health.

Figure 7 displays the training performance metrics of the LSTM model over a series of epochs. This shows how the accuracy of the model changes with each training epoch. The proposed model obtained an accuracy of 99.57%. It also shows the training loss, which measures how well the model's predictions match the actual target values during training. Lower values indicate better performance. The proposed model achieves 0.0347 of loss. Figure 8 illustrates a sample conversation between a patient or user and the chatbot model designed to monitor emotional health. It showcases how the chatbot responds to user input, providing an example of a simulated interaction. The conversation includes user queries and the chatbot's generated responses, demonstrating the chatbot's functionality.

## 5. CONCLUSION

In conclusion, the implementation of an LSTM-based chatbot designed to monitor emotional health and identify individuals at risk of psychological disturbances represents a significant step forward in the utilization of technology for mental health support. This chatbot showcases its ability to effectively engage in conversations with users and provide responses based on patterns learned from the 'intents.json' dataset. This highlights the potential of natural language processing (NLP) techniques to comprehend and address user emotions and concerns, offering a unique avenue for mental health assistance. One of the standout features of this chatbot is its capability to detect individuals at risk of psychological disturbances. By analyzing user input, it can promptly identify potential issues, enabling timely intervention and support. This proactive approach holds the promise of early intervention, which is crucial for preventing the escalation of mental health challenges and ensuring individuals receive the necessary assistance when they need it most.Moreover, the accessibility offered by chatbots is a key advantage. Users can comfortably express their emotions and seek help through this platform, which can alleviate some of the barriers and stigma associated with discussing mental health concerns. This accessibility aspect is especially valuable in reaching individuals who may be hesitant to seek help through traditional channels. Additionally, the chatbot system has the potential to amass a substantial dataset of user interactions. Analyzing this data can yield valuable insights into user behavior, common mental health issues, and the effectiveness of various interventions. Such data-driven insights can inform the ongoing development and refinement of mental health support systems.

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