



Project 4

Mental Health Chatbot

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Project Vision and Overview



Imagine having a friend who's always there to listen to how your day went, whether it was good, bad, or just meh. That's the spirit behind our project. We wanted to create something simple yet meaningful—a chatbot that offers a listening ear to anyone needing to share their feelings at any moment. Our goal wasn't to replace human conversation but to offer a stepping stone towards understanding and managing our emotions.

Our chatbot, although not capable of holding deep, therapeutic conversations, serves as a comforting presence. If you tell it you're feeling happy, it'll cheer along with you, saying, "That's great to hear!" It's our way of dipping our toes into the vast ocean of mental health support, using technology. Through this chatbot, we aim to make the first step in seeking emotional support as easy as sending a message to a friend. This presentation is our journey in creating a chatbot that, in its own simple way, brings a bit of light to someone's day. Join us as we explore the insights, challenges, and the heartfelt moments that this project has brought into our lives.

Gathering the Data

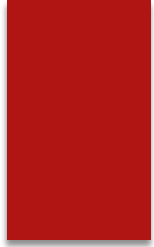
Before designing our LLM we wanted to look at mental health statistics in the United States. We found a CSV file detailing the average amount of recent mentally unhealthy days for adults in the US from 2011-2021. It further detailed this data for race and gender in each state.

Cleaning the Data

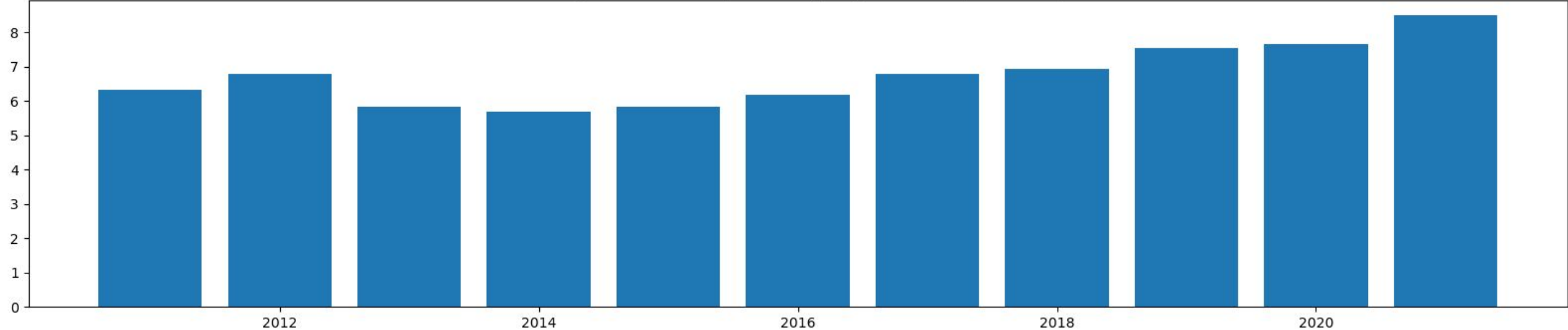
The data in our CSV file was not very clean to start, as it was not organized by state or year, and gender and race/ethnicity fell under the same column. To clean it up we made two separate DataFrames, one displaying the average amount of recent unhealthy days by gender, and the other by race or ethnicity. We then sorted the data by state and year and dropped any columns and rows with data we were not using.

Analyzing the Data

After analyzing the data from our dataframes we found that as a whole, mental health seemed to decline over the ten years the data reviewed, as adults saw an average of about 6.5 recently mentally unhealthy days in 2011 to around 8.5 in 2021. We also saw that females on average saw more mentally unhealthy days than men.

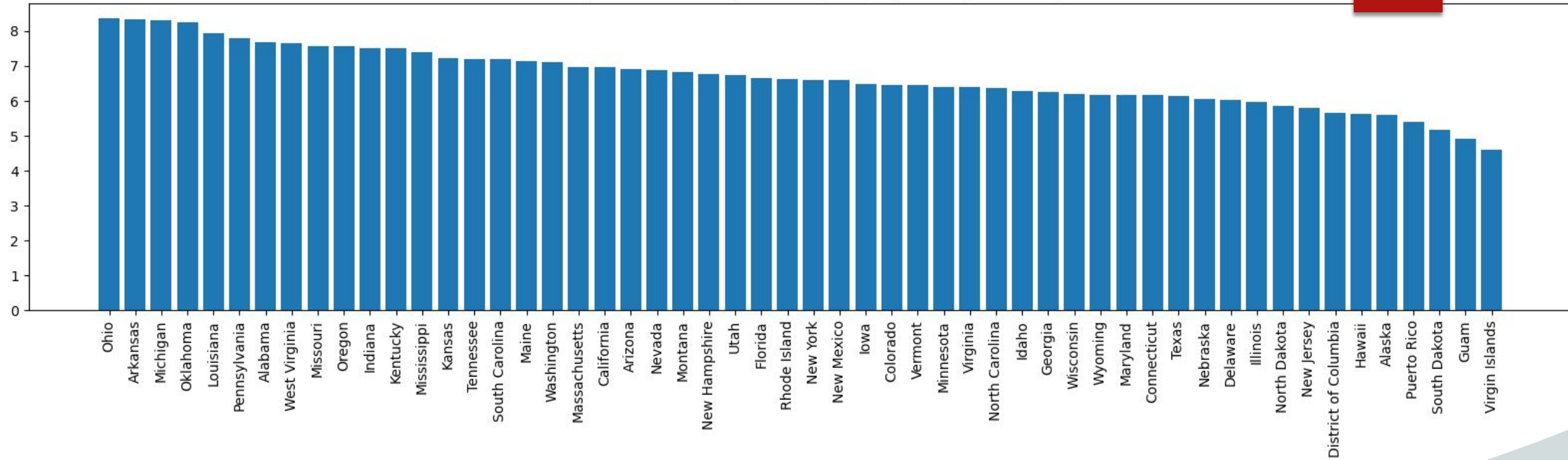


Average Recent Mentally Unhealthy Days for Adults (2011-2021)



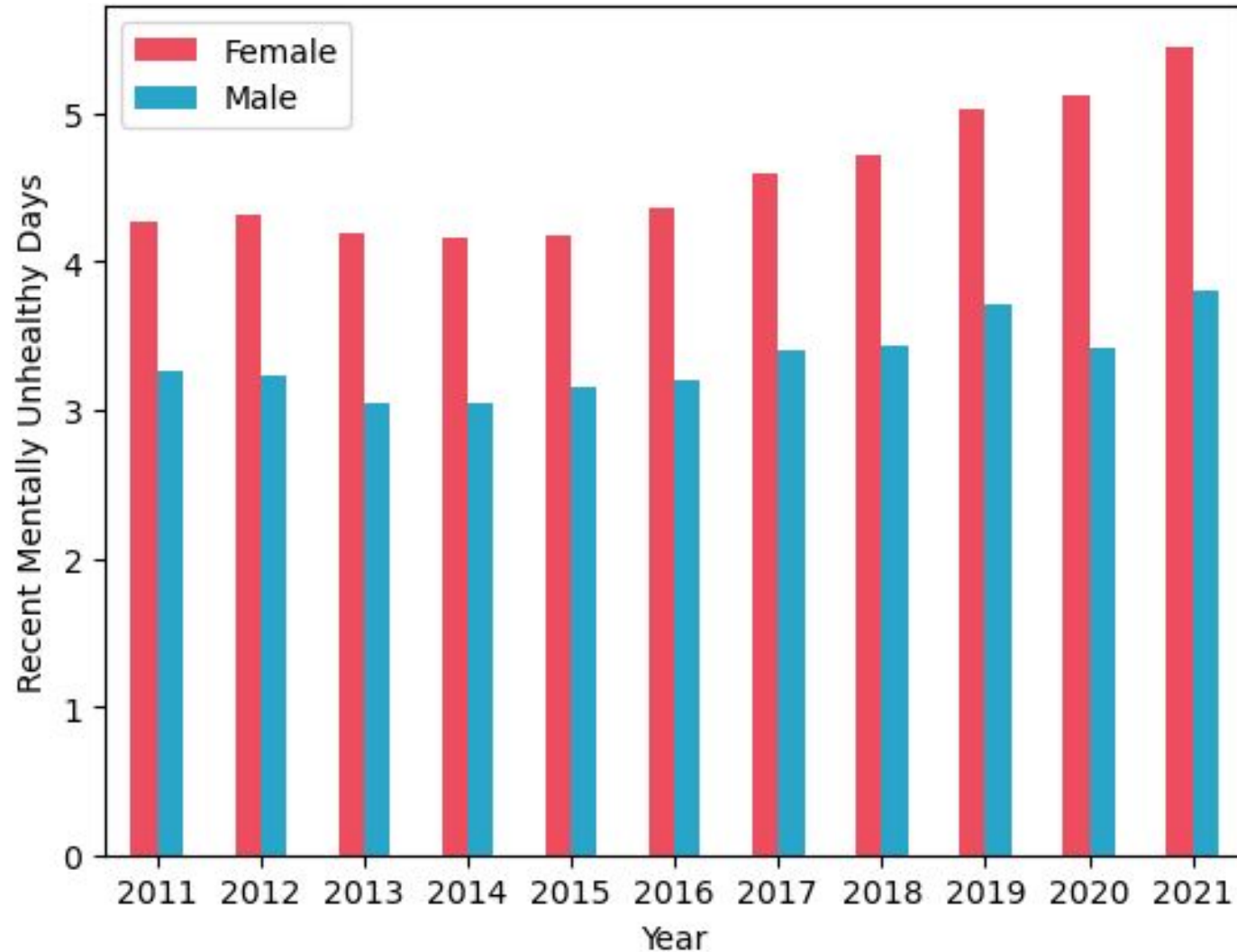
Average Recent Mentally Unhealthy Days for Adults in US

Average Recent Mentally Unhealthy Days by State (2011-2021)



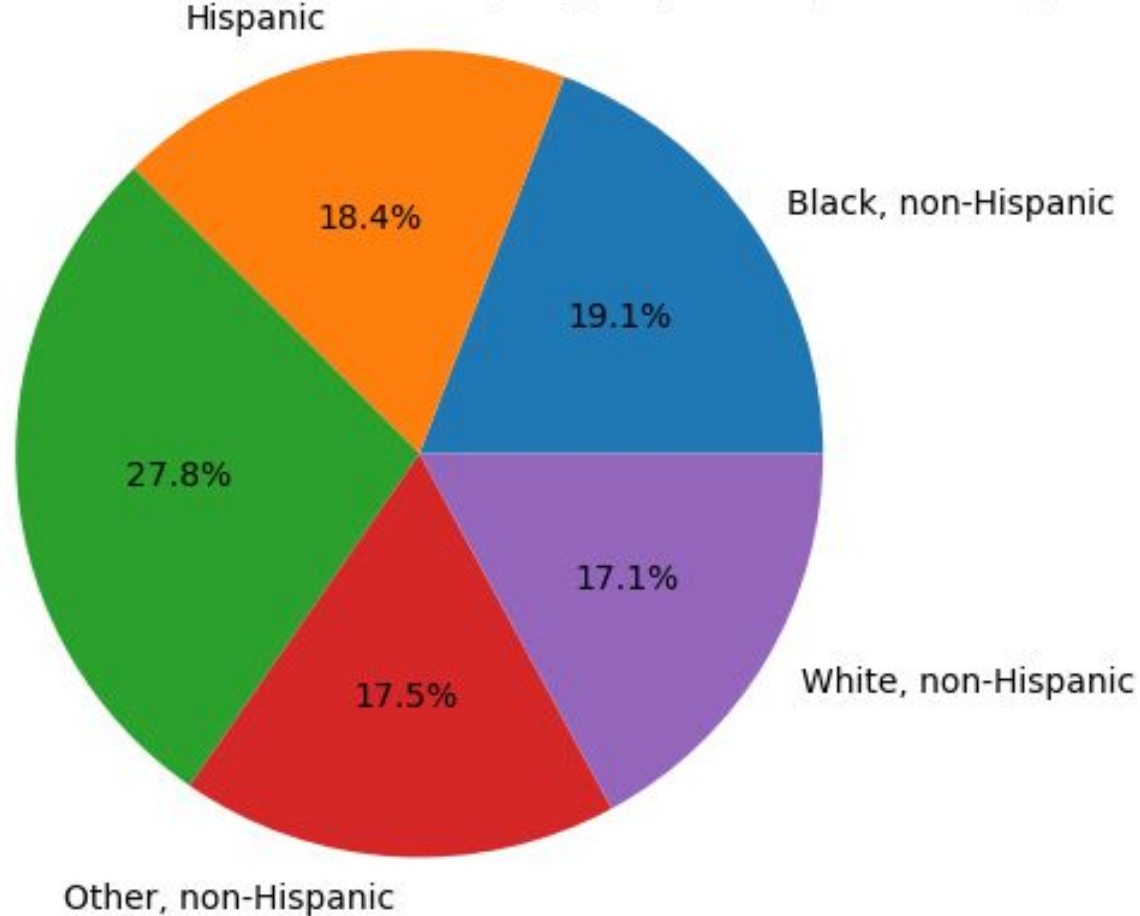
Average Mentally Unhealthy Days by State

Average Recent Mentally Unhealthy Days per Year



Average
Recent
Mentally
Unhealthy
Days per Year
by Gender

Average Recent Mentally Unhealthy Days by Race (2011-2021)



Most Recent
Mentally
Unhealthy Days
Breakdown by
Race/Ethnicity

Creating the Model

After analyzing the mental health data, we began work on our chatbot. To create our model we first found a JSON file with various prompts and responses to get responses for our model to give the user. We used WordNet Lemmatizer from the NLTK library to group variants of the same word. We initialized the model with 2 hidden layers along with 2 dropout layers to prevent overfitting. The hidden layer used the ReLU activation function and the output layer uses Sigmoid.

Training the Model

To train our mental health chatbot, we started with organizing and processing our data from A JSON file that contained various user inputs and corresponding responses. Using the NLTK library, we broke down the inputs into simpler, base forms and removed any unnecessary punctuation to standardize our data. This process allowed us to create a structured dataset where each input was transformed into a numerical format that the chatbot could understand a technique known as bag of words. We then designed the chatbot's brain using TensorFlow, layering it with Dense layers for processing and Dropout layers to prevent overfitting.

Model Performance

After testing the model, it came out with an accuracy of about 74%, and would give pretty accurate responses based on what the user asked it. However, it was a bit case-sensitive and sometimes could not understand the user based on the casing of their typed message.

```
15/15 [=====] - 0s 803us/step - loss: 1.9767 - accuracy: 0.7416
```

```
Test Accuracy: 74.16%
```

```
15/15 [=====] - 0s 718us/step
```

```
Confusion Matrix:
```

```
[5 0 0 ... 0 0 0]
```

```
[0 5 0 ... 0 0 0]
```

```
[0 0 3 ... 0 0 0]
```

```
...
```

```
[0 0 0 ... 5 0 0]
```

```
[0 0 0 ... 0 5 0]
```

```
[0 0 0 ... 0 0 6]
```


Conclusion

Through lots of testing our model gradually began improving performance and giving better responses to the user. The chatbot was eventually able to pick up on the user's feelings and emotions and give appropriate responses to help the user feel better. It is definitely no replacement for a real therapist, but it can offer the user some help, which was the goal.