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# Title: Virtual Counseling using AI, ML and NLP

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**Faculty: Dr. Tulasi Prasad Sariki** **Sign:**

**Date:**

# BONAFIDE CERTIFICATE

Certified that this project report entitled **"Virtual Counseling using AI, ML and NLP"** is a bonafide work of **Lavansh Arora (20BCE1046)** who carried out the project work under my supervision and guidance for the course **CSE 4020 - Machine Learning.**


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# CONTENTS

# ABSTRACT

As per WHO’s definition, “Health is a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity”. And yet, mental health is still struggling to be recognized as an important part of the overall well-being of a person. The awareness regarding the same is an ongoing effort to reduce the stigma around mental illness and mental health conditions by showing individuals respect and acceptance removes a significant barrier to successfully coping with their illnesses. Majority of the people deal with a lot of stress on a daily basis. Some people react to stress by feeling ill, stuck, or overwhelmed, while others feel depressed, anxious, or scared. People often spend a lot more time worrying, feeling guilty, or feeling ashamed for not accomplishing the things they feel they should or could be doing. Mental health disorders are hard to be diagnosed as well. Even though one might feel something is wrong with them, they don’t express or open up to people around them in fear of disapproval by family or friends. Today, as the need for mental health services continues to surpass availability, people in distress can reach out online to mental health chatbots. In other words,  Our aim is to provide a solution that includes user-friendly communication, stress detection, along with virtual consultancy in order to make the users feel better. Artificial Intelligence (AI), Machine learning (ML) models and Natural Language Processing (NLP) is used to analyze the user's dialogue to determine how the person is feeling. This information is then utilized to further provide consultation based on the severity of the situation and hopefully make the person feel better by opening up to our AI therapist.

## KEYWORDS

AI therapist, mental health chatbot, virtual therapy, cognitive behavioral therapy (CBT), confidence level, intent, encouragement.

# INTRODUCTION

Mental health is a significant global challenge that affects millions of people worldwide. It refers to a person's overall psychological well-being, including their emotional, social, and cognitive functioning. Good mental health allows individuals to manage daily stressors, maintain healthy relationships, and make meaningful contributions to their communities. It is essential to prioritize mental health and seek support when needed, as untreated mental health conditions can significantly impact an individual's quality of life and can lead to even more severe complications. According to the World Health Organization (WHO), approximately 1 in 4 people globally experience mental health issues at some point in their lives.

Depression is the major cause of disability with over 264 million people being affected globally. Furthermore, anxiety disorders are the most common mental illness in the United States, affecting approximately 40 million adults each year. Moreover, suicide is a leading cause of death worldwide, with one person taking their own life every 40 seconds.

A student's overall well-being, interpersonal relationships, and academic performance can all be adversely affected by depression. Despite the fact that many colleges offer free mental health services to students, a significant number of students choose not to seek assistance for a variety of reasons, including lack of knowledge about mental health, stigma attached to those who do so, and due to lack of resources. The COVID-19 pandemic has made mental health issues among young adults more common due to a number of factors including life uncertainties and financial pressures.

The potential of technology to assist and improve young people's mental health, has been recognised by health organizations, researchers, and professionals. These technologies include mobile phone applications, internet resources, programs etc. Online courses, tools available for self-diagnosis, peer support through online forums, video and audio therapy sessions with counselors are all accessible through web-based services. Such technologies are gaining immense popularity especially among the young generation due to the fact that they are the ones who are more likely to commit suicide as a result of depression.

Recently, conversational agents such as chatbots including Google Assistant, Siri, Alexa etc. have also attracted people’s attention. Such chatbots are capable of conversing with the individual just like a normal human being, enabling people to share feelings with them as well as get appropriate counseling. Moreover, an increasing number of chatbots with a focus on mental health are available these days, targeting a range of mental health issues and performing diagnosis as well as providing counseling. For instance, the Woebot chatbot was helpful in reducing symptoms of stress and anxiety within two weeks. Also, the Wysa chatbot helped to reduce the level of depression among youngsters.

Therefore, our project aims to develop a virtual counseling platform that will provide virtual therapy to people, especially those who are suffering from depression and anxiety and who hesitate to seek mental help because of the social stigma prevailing in the society.

## MOTIVATION

Mental illness is a significant global challenge and is the leading cause of disability worldwide. India faces a particularly daunting challenge due to its cultural complexity and a severe shortage of mental health professionals. There are only 0.75 psychiatrists available for every 100,000 patients, and mental health conditions are predicted to cause significant economic losses globally. Studies show that India accounts for a significant percentage of global suicides, yet nearly half of the population has no access to mental health facilities within a 20km radius and lacks awareness of their existence. Thus, the efforts to provide free access to therapy in India are crucial in addressing the mental health crisis in the country. With the severe shortage of mental health professionals, and the stigma associated with mental illness, many people in India do not have access to the care they need. The virtual platform provided by our project can thus provide a safe and accessible space for people to seek help without the fear of being judged.

The proposed solution hence seeks to alleviate this issue by providing ease of access to therapy at no cost. Also, it is more approachable than interacting with human beings as there is more control in starting and stopping a conversation.
Virtual counseling allows individuals to access therapy from the comfort of their own homes. This is particularly helpful for individuals who have limited mobility, live in rural or remote areas, or have difficulty leaving their homes due to social anxiety or other issues.
It also eliminates the need for individuals to travel to appointments, take time off work, or arrange for childcare, thereby making it easier for individuals to fit therapy into their busy schedules.
More so, it can provide a sense of anonymity that some individuals may find more comfortable than in-person therapy. This can make it easier for individuals to open up and discuss sensitive topics, such as depression and other mental health issues.
It can even be more affordable than in-person therapy, as it eliminates the need for therapists to maintain physical office spaces and may allow therapists to see more patients in a day.
Virtual counseling can be customized to fit the needs and preferences of individual patients. For example, some individuals may prefer to communicate via video chat, while others may prefer messaging or phone calls. This flexibility can help ensure that individuals receive the type of support that works best for them.
Overall, virtual counseling can be a powerful tool for treating depression and other mental health issues, as it provides accessibility, convenience, anonymity, affordability, and customization.

## Objectives

The objectives of our project include:

- To develop a virtual counseling platform that utilizes artificial intelligence (AI) and natural language processing (NLP) technologies, and helps overcome depression and anxiety, thereby, reducing the suicidal tendency of a person.
- To design an AI-powered chatbot that can provide 24/7 counseling support to clients, allowing them to access help whenever they need it, which is not so in the case of mental health professionals.
- To build a system that is user-friendly and hence makes it easier for people to utilize its benefits. People suffering from mental health disorders can simply talk or chat with the bot about their feelings. They would then be provided with the necessary counseling.
- To design a platform which can be accessed by anyone from anywhere, and thus there would be no need to physically go to a professional or health center for seeking mental help.
- To develop a system that can provide support during mental health emergencies, such as suicidal ideation or severe anxiety or depression. If any person comes across suicidal thoughts, he/she may not find it appropriate to consult a mental health expert, rather, he/she can talk to the chatbot and seek help without letting anyone know about it. It will thus provide counseling to the user and will also be helpful in reducing the stigma associated with seeking counseling services.
- To design a system that can provide mental health support at almost no cost, making it more accessible to individuals who may not be able to afford traditional therapy or counseling services, since they are usually expensive.

## Review of Literature:

The study conducted by **Lie H., et al. (2022)[1]** compared the effectiveness of chatbot therapy and bibliotherapy for treating depression and found that chatbot therapy is a practical and affordable self-help intervention that can provide interactive support for people with depression. The research involved 83 university students who were randomly assigned to either a chatbot test group or a bibliotherapy control group. The chatbot group received a chatbot-based intervention, while the control group received a minimal level of bibliotherapy. The participants completed a set of questionnaires to measure the levels of anxiety and depression. Through the study, it was concluded that self-help intervention for depression, delivered through a chatbot, was more effective than a basic level of bibliotherapy. This was evidenced by a reduction in depression and anxiety symptoms.Thus, the study suggests that chatbot offers more personalized and immediate support compared to bibliotherapy, and can be an affordable alternative to traditional therapy.

**Kour, H et. al (2022)**[2] proposed a methodology for effectively determining if a user is experiencing depression based on their tweets. The objective of the study was to identify the individuals who are likely to have suicidal tendencies, and to provide them with support from friends, family, and mental health professionals. The methodology involved extraction of user tweets from Twitter, following which, data cleaning was performed on the raw text. Text data was then transformed into numerical format using hybrid embedding technique of TF-IDF and fastText. SVM and Random Forest classifiers were chosen to categorize the tweets as 'Depression,' 'Suicidal,' and 'Teenager (normal). The accuracy achieved for depression prediction by SVM was 75% and by random forest was 71%. However, the study has limitations, such as the reliance on self-reported data from online forums and social media, which may not be representative of the general population. The authors also suggest the need for further research to validate the findings and explore the ethical implications of using NLP and ML for mental health prediction.

The research conducted by **Koulouri, T, et al (2022)**[3] aimed to determine whether chatbots could be an acceptable solution for mental healthcare for young adults. To achieve this, the researchers used three research activities: a survey study to explore young adults' mental health issues and perceptions of mental health technology, a literature review to analyze current empirical evidence on the acceptability of mental health chatbots, and interviews with mental health professionals to gain insights into the acceptability of chatbots. The study found that chatbots can be highly effective in providing mental healthcare and hence designed a prototype of a chatbot that offered mental health benefits such as cognitive behavioral therapy skills, relaxation and breathing techniques, mindfulness, and meditation. The researchers concluded that chatbots can be a useful solution for young people who need timely mental health support, especially when professional services are not available due to high demand and limited healthcare budgets.

**Campbell, E. L., et al (2022)**[4] talk about mental health meaning our emotional, psychological, and social well-being. Stress, depression, and anxiety are some of the negative manifestations in our every-day-life. Major Depressive Disorder (MDD) is a common mental health disorder frequently linked to increase in suicidal and self-destructive behaviours. In this regard, this paper proposes speech- and text-based systems using the Distress Analysis Interview Corpus-Wizard-of-Oz (DAIC-WOZ) dataset as an experimental framework.. On the other hand, the text-based system is based on GloVe (Global Vector) features and a Convolutional Neural Network (CNN) as a classifier. The S2S architecture provides mostly better results than previous speech-based systems, indicating that speech is a useful source of information for the detection of MDD. However, the GloVe-CNN system showed even better performance, leading to the idea that text is a more suitable information source for the detection of MDD when it is manually developed. Nevertheless, it is not a straightforward task to obtain high-quality transcriptions automatically, which makes the development of effective speech-based systems necessary.

**Jackson, R. G. et al (2017)**[5] aimed to develop a tool that could identify and extract symptoms from clinical records, potentially improving diagnosis and treatment of severe mental illness (SMI). The authors discuss the challenges in extracting information from clinical records, such as the sheer volume of data and the variation in language used by healthcare professionals. NLP techniques offer a promising solution to these challenges and describe the development of their tool, called CRIS-CODE. The paper then involves training and testing the CRIS-CODE tool on a dataset of clinical records from patients with SMI. The authors explain the pre-processing steps used to clean and standardize the text data and the machine-learning algorithms used to classify symptoms. The results of the study show that the CRIS-CODE tool was able to accurately extract symptoms from clinical text, achieving a high F1-score of 0.92 for identifying hallucinations and delusions. The authors also discuss the limitations of their study, such as the need for further testing on different datasets and the potential bias introduced by the use of certain diagnostic codes. Finally, the authors conclude by discussing the potential applications of the CRIS-CODE tool, such as improving the accuracy of diagnosis and enabling more targeted treatment for severe mental illness. The authors highlight the importance of further research in this area to validate the tool's performance and ensure its ethical and clinical appropriateness.

**Le Glaz et al. (2021)[6]** summarize and characterize machine learning and NLP techniques used in studies for mental health and also consider the potential use of these methods in mental health clinical practice. Recently, Machine learning (ML) and natural language processing (NLP) have gained significant attention in medical research and are viewed as a new approach. The search for this study was conducted using 4 medical databases (PubMed, Scopus, ScienceDirect, and PsycINFO) with the keywords: machine learning, data mining, psychiatry, mental health, and mental disorder. Another primary source of data was social media. Standard NLP methods were utilized in preprocessing, and a dedicated unique identifier extraction was applied to medical texts. The preference was for efficient classifiers rather than transparent functioning classifiers. Nevertheless, these techniques have a tendency to confirm existing clinical hypotheses rather than generate entirely new insights, and their application is limited to a specific population (such as social media users).

Additionally, language-specific characteristics can enhance the performance of NLP models, and it is important to investigate their application to other languages more thoroughly. However, these techniques can extract valuable information from unexplored data sources (such as patients' daily habits that are typically inaccessible to healthcare professionals). Nonetheless, ethical considerations also need to be addressed before implementing these techniques as an additional tool for mental health care. While machine learning and NLP have the potential to provide multiple perspectives in mental health research, they should be viewed as tools to support clinical practice.

**M. Czerwinski, J. Hernandez and D. McDuff in their study "Creating an AI That Feels: AI systems with emotional intelligence could learn quicker and be more helpful" (2021)[10]** presented the idea of creating AI systems with emotional intelligence that might be able to learn more quickly and provide more assistance than existing systems. According to the report, AI systems with emotional intelligence could identify user frustration or confusion and modify their replies accordingly. They could also offer emotional support to people who are dealing with mental health difficulties or assist those who are trying to manage stress and anxiety. The paper stressed on the importance of carefully weighing the ethical implications of developing emotional intelligence in AI systems and making sure that they are created and used in ways that support human welfare and respect personal privacy and autonomy.

**S. Rahman (2023)[11] in their paper "AI-Driven Stroke Rehabilitation Systems and Assessment: A Systematic Review"** aimed to conduct a systematic review to assess the effectiveness of AI-driven stroke rehabilitation systems and assessments. The studies demonstrated that AI-driven rehabilitation systems have the potential to improve stroke rehabilitation outcomes by providing personalized and adaptive interventions. The studies reviewed showed improvements in motor function, balance, and activities of daily living. The authors also found that AI-driven assessment tools could be used to provide more objective and accurate assessments of stroke patients' conditions. However, the authors noted that more research is needed to determine the long-term effectiveness and feasibility of AI-driven rehabilitation systems and assessments.

**Isewon et al.(2015)[12]** designed and implemented a text-to-speech conversion system for visually impaired people. They conducted listening and comprehension tests with visually impaired users, showing that the synthesized speech was clear and understandable. The authors suggested possible future work to improve the system's performance, such as incorporating machine learning techniques to improve text analysis and speech synthesis accuracy.It highlighted the potential of text-to-speech synthesis technology to improve accessibility and functionality across various platforms, such as telephony systems, ATM machines, and video games. This demonstrated the potential for text-to-speech synthesis technology to have had a significant impact on improving accessibility and inclusivity in various domains.One potential drawback stated in the system that it is not always capable of accurately reproducing the intended speech, especially when the input text contained complex or nuanced language. Hence, can create confusion or misunderstanding on the part of the listener.

**Patel F. et al (2019)[13]** proposed the ideology of a social therapeutic chatbot that provides mental relief to students who undergo different levels of stress. The chatbot was capable of analyzing the text of users' conversations and categorizing them based on different emotions, such as happiness, joy, shame, anger, disgust, sadness, guilt, and fear. Additionally, the chatbot used the emotion data to identify the users' mental state, i.e whether they are feeling stressed or depressed. The researchers used three neural networks for classification namely Convolutional Neural Network (CNN), Recurrent Neural Network (CNN), and Hierarchical Attention Network (HAN). The ISEAR dataset was used for emotion detection in text. The complete process consisted of several stages including tokenization, word vector formation, embedding’s, use of neural networks for classification and identification of mental state. The accuracy achieved in case of CNN was 75% and that in case of RNN and HAN was 70% accuracy for 15 epochs.

## Research gap & Novelty

The researchers who have previously designed bots for mental help have mainly used a Deep Learning or Neural Network approach. Among neural networks, Convolutional Neural Network (CNN), Recurrent Neural Network (CNN), and Hierarchical Attention Network (HAN) were used (Patel F. et al (2019)). Also, some of the researchers have used SVM and Random Forest

( Kour, H et. al (2022)). However, in our proposed model, we have made use of sequential networks like RNN (Recurrent Neural Network (RNN)as well as Long Short-Term Memory (LSTM).

RNNs are better suited for analyzing sequential data, such as text, which was used in our model, as compared to CNN. Also, RNNs can map out many-to-many, one-to-many, and many-to-one input and outputs, which is not possible with other algorithms that deliver one output for one input**.** Hence, since we used RNN, we were able to map many input sentences with similar meaning to multiple output sentences, which thus helped in efficient development of the chatbot.

More so, the use of LSTM allows us to generate more diverse dialogues using low-resource conversational data. Typically, traditional conversational chatbots use a retrieval-based model that depends on a significant amount of conversational data to match user intents with appropriate responses. This model involves storing predefined responses in a database and retrieving them based on the similarity between the user input and the stored responses. On the other hand, LSTM networks rely on internal cell gates to selectively remove or add information from the cell state based on input values, thereby allowing them to better understand the context of a conversation and hence generate more natural responses. Thus, LSTM-based chatbots can provide a more personalized and engaging experience for users as compared to other neural networks.

Furthermore, most of the researchers have built the model using a single dataset. On the other hand, we have developed the virtual platform using a combination of multiple datasets (from Kaggle) in order to attain a higher accuracy.

## Proposed work and Methodology:

We have used multiple datasets from kaggle, links to which have been provided in the modules section, in order to train the model. The required preprocessing (tokenization, label encoding etc.) was carried out on the data, following which, the model was trained. We have used both RNN as well as the LSTM network for training the model.

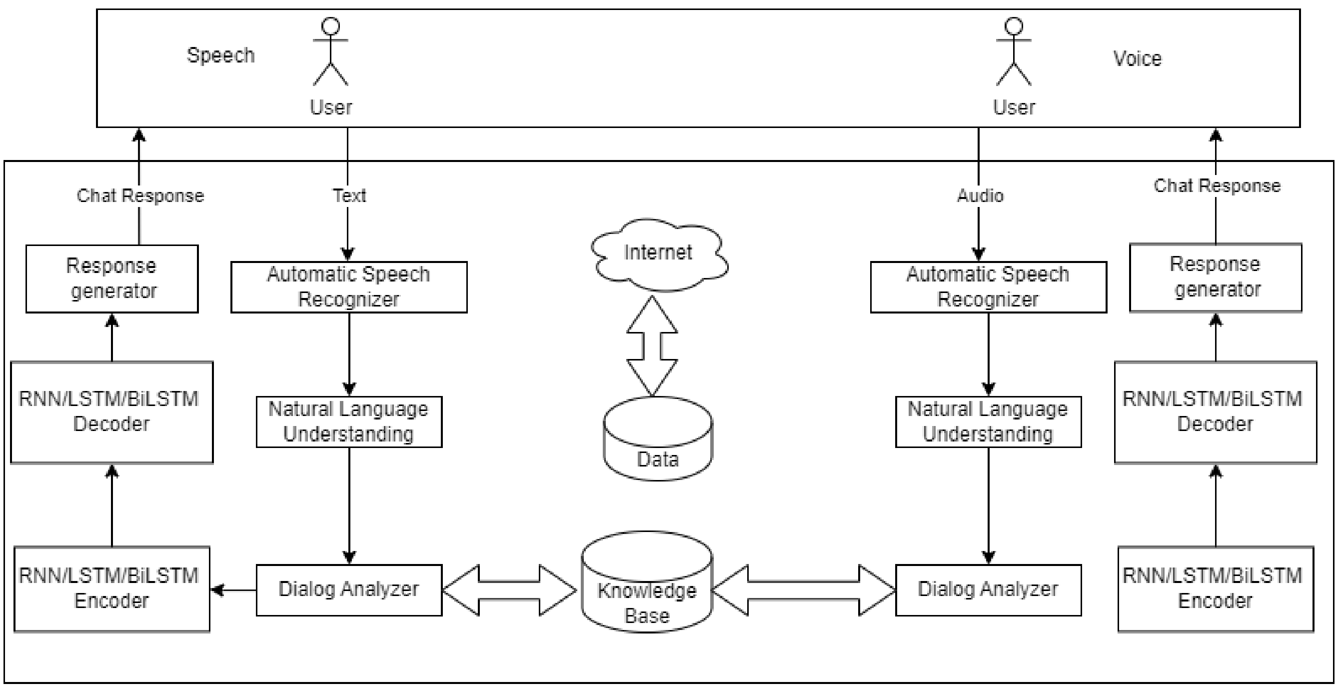
The system is designed to receive text or speech messages from the users and analyze them in order to understand what the user wants to communicate. Upon analyzing, it generates a suitable response, which could vary from cheering up the user, in case he is depressed or providing jokes, if he is sad. It even encourages the user to open up and talk so that it can understand the emotions and feelings and provide appropriate counseling. The system also persuades the user to go for a mental health check up if needed.

In our system, we have incorporated both text as well as voice modules, i.e the user can either talk to the system or can chat with the bot and describe his/her feeling, and can get the required help. Once the user's intent is identified (either via text or voice) , the system uses a predefined list of responses (as per the model) in order to provide an appropriate answer or guidance. For example, if a user expresses that they are feeling depressed, the system will identify the intent and access the corresponding responses related to depression. These responses can include advice on how to deal with depression, suggestions on where to find professional help, or words of encouragement.

Furthermore, in the voice module, as we speak, the system calculates the confidence level for all probable sentences and selects the most likely sentence (i.e the one with the maximum confidence level).

Hence, by utilizing machine learning algorithms and natural language processing, the system can accurately determine the user's intent and provide appropriate help or counseling.

## Architecture Diagram and Explanation




Our project consists of two modules - chat and voice, i.e. the user is given an option to choose to text or talk to the chatbot. After choosing the desired option, the chatbot asks for a user response to know how they're feeling currently. Then the user response is recognized using automatic speech recognizer. Using natural language understanding, the intent in the user's message is analyzed and a random response is generated from the dataset. A machine learning model is used to encode and decode the user's feelings and provide necessary response to make the user feel better and not take any drastic step in case they feel very low.

## Technical Requirements

### Software Requirements:

The following tools and packages were used in our project to develop the virtual counseling system:

- Python
- TensorFlow
- Keras
- NLTK
- Scikit-learn
- Pyaudio
- Webbrowser
- Pyttsx3

# MODULES

## Module 1: Data collection

A combination of multiple datasets was used to train the model in order to achieve a higher accuracy. The datasets were collected from kaggle.

Mental Health Conversational Data:

https://www.kaggle.com/datasets/elvis23/mental-health-conversational-data

This dataset includes basic conversations, FAQs about mental health, conversations from traditional therapy, and general guidance that can be given to people with anxiety and depression.

The dataset contains intents, which is the intention behind a user's message. Also, there are a set of Patterns and Responses appropriate for each intent. Patterns are examples of user messages that match with his/her intent, whereas Responses are the chatbot's responses that match the user's intent.

Mental Health FAQ for chatbot:

https://www.kaggle.com/datasets/narendrageek/mental-health-faq-for-chatbot

This dataset consists of FAQs about mental health

## Module 2: Data preprocessing

This stage consisted of label encoding as well as tokenization.

Label encoding: It is the process of converting categorical data into numerical data.

The tags in the dataset were appended to a list called training labels, which included ‘greeting’, 'morning', 'afternoon', 'evening', 'night', 'angry' etc. Since all these values are categorical, they were converted to numerical data using the LabelEncoder() function. For instance, greeting was encoded as 44, morning as 55, afternoon as 1 and so on.

Tokenization: It involves breaking a text into smaller units called tokens. These tokens can be words, phrases, or even characters.

In this project, tf.keras.preprocessing.text.Tokenizer() was used:

- It removes all punctuation
- It converts the text into space-separated sequences of words
- The sequences are then split into lists of tokens.
- The tokens are then indexed (i.e converted to integer)

The tokenizer was used with two arguments:

- Num_words: It specifies the maximum number of words to be kept
- oov_token: It is used to replace out-of-vocabulary words (i.e unknown words)

The tokens were then converted into integer sequences using Tokenizer.texts_to_sequences().

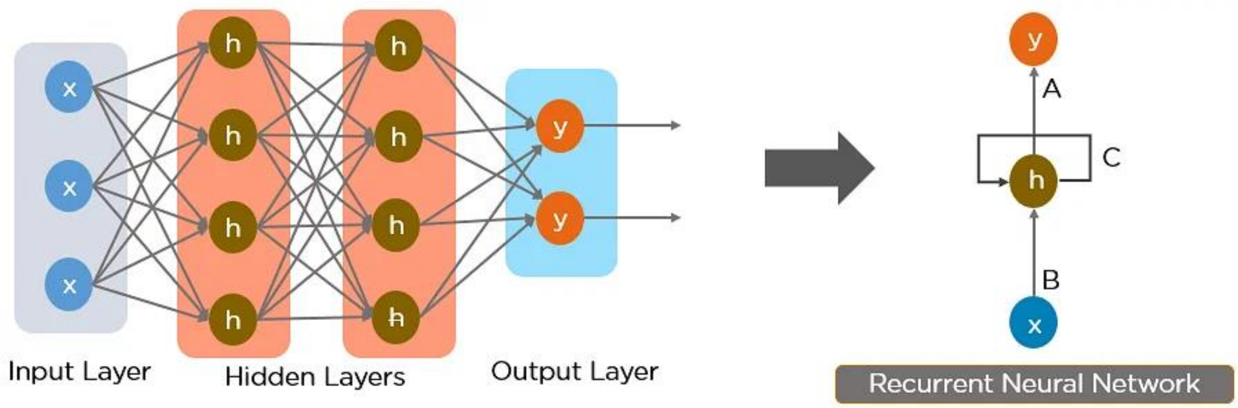
keras.preprocessing.sequence.pad_sequence() was used to pad all texts into a uniform length, since they vary in length.

## Module 3: Model Building

Since the dataset contains text which is a sequence of data, Sequential models (RNN and LSTM) were used.

### A. Using Recurrent Neural Network (RNN)

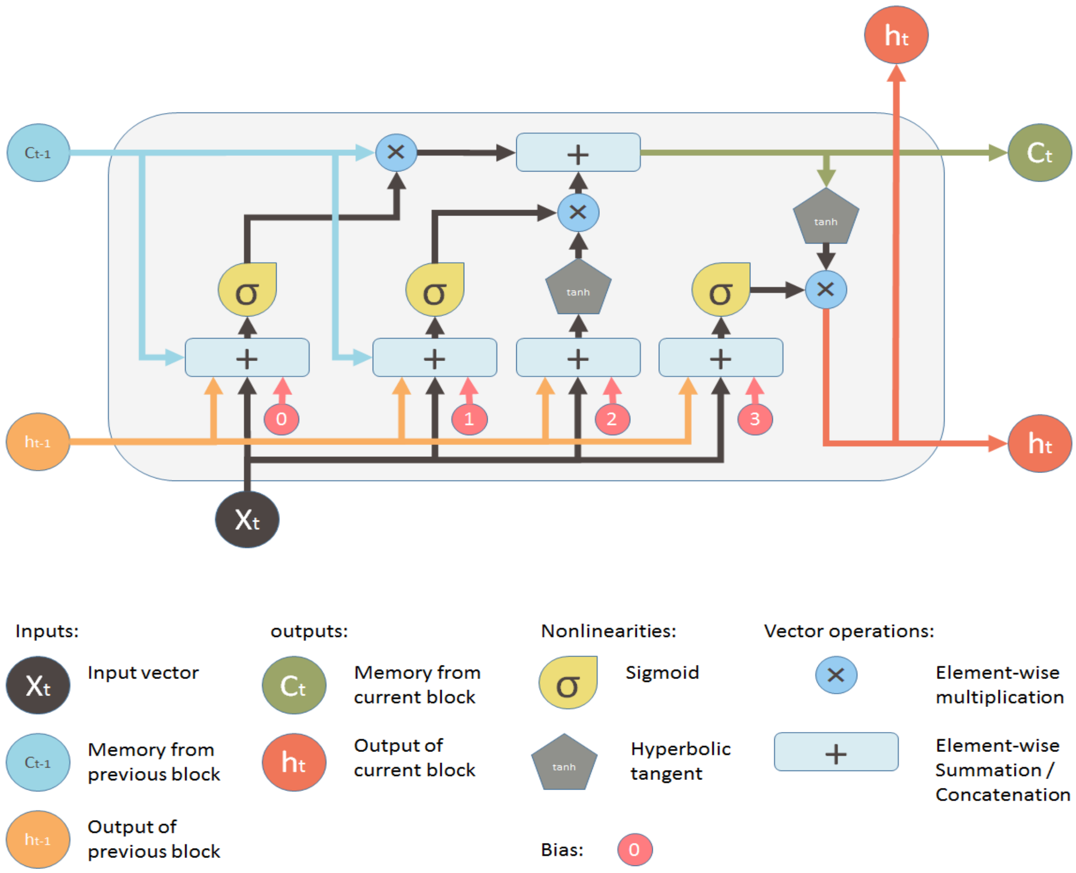
RNN is a type of neural network that can process sequential data, such as text, by maintaining a hidden state that captures the context of the conversation. The encoder RNN conceives a sequence of context tokens, one at a time and updates its hidden state. After processing the whole context sequence, the decoder RNN generates a response, one token at a time, conditioned on the context.




- Firstly, a sequential model using Sequential() function.
- Next, an Embedding layer is added which converts each word into a fixed length vector of defined size. Here, there are three parameters:
    - vocab size: Size of the vocabulary.
    - embedding dim: Dimension of the dense embedding.
    - input length: Length of input sequences.
- Next, a GlobalAveragePooling1D layer is added which averages across the vectors to flatten it out.
- Afterwards, a Dense hidden layer with 16 neurons is added. It will use the ReLU activation function.
- Another Dense hidden layer with 16 neurons is added, also using the ReLU activation function.
- Finally, a Dense output layer with the number of neurons being the same as the number of tags in the dataset (i.e one per class) is added. The softmax activation function is used in this layer since the classes are exclusive

## B. Using Long Short-Term Memory (LSTM)

It is a type of recurrent neural network that is used to generate more diverse and natural dialogues. LSTM networks have feedback connections that allow them to process entire sequences of data, unlike standard feedforward neural networks that can only process single data points. LSTMs are designed to prevent the neural network output from either decaying or exploding as it cycles through feedback loops, which makes them better at pattern recognition than other neural networks. LSTM networks rely on internal cell gates to selectively remove or add information from the cell state based on input values, which allows them to better understand the context of a conversation, thereby generating more natural responses.



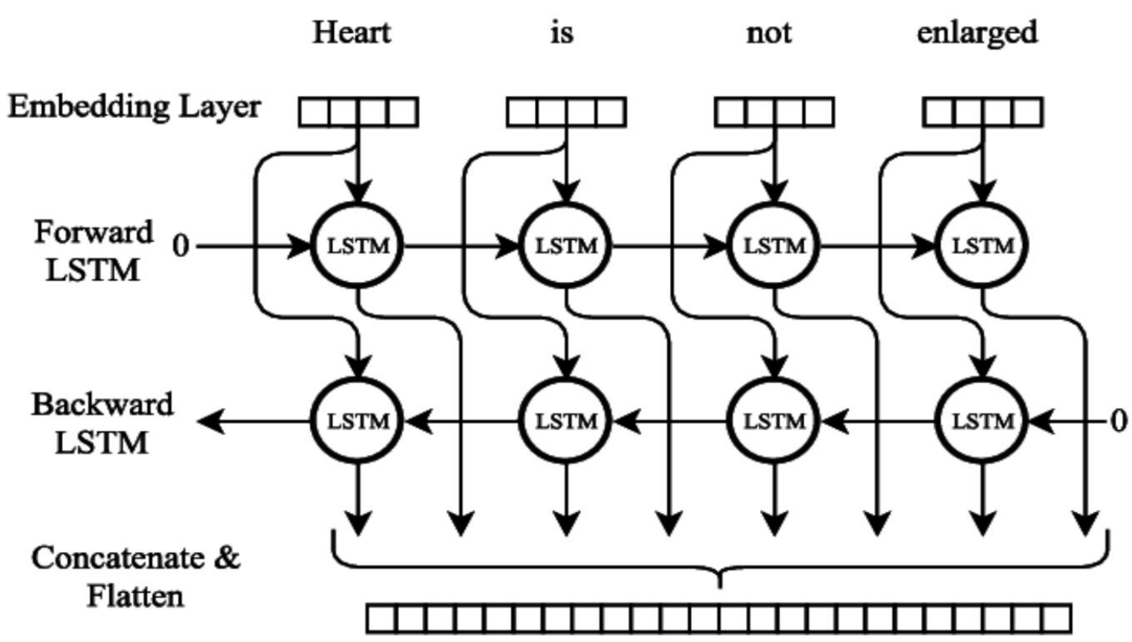

a. At a high level, the LSTM model works by processing input sequences of data through a series of gates that regulate the flow of information. These gates include **an input gate, output gate, and forget gate**, which determine which information from the input sequence is relevant and should be remembered or discarded.
b. More specifically, at each time step in the input sequence, the LSTM cell takes in the input vector and the previous cell state and decides what information to keep or forget. This is done through the input gate, which controls the amount of new input to let in, the forget gate, which controls what information to keep from the previous cell state, and the output gate, which controls the amount of output to produce.
c. The LSTM model uses memory cells to store information over time, and the input and forget gates regulate the flow of information into and out of these cells. The output gate then determines the amount of information to output from the cells.
d. The weights and biases of the LSTM model are learned through training on a labeled dataset, and the model is typically optimized using gradient descent or other optimization techniques.

So jumping on to the implementation of this model:

e. Firstly, a sequential model using Sequential() function.
f. Next, an Embedding layer is added which converts each word into a fixed length vector of defined size. Here, there are three parameters:
    - vocab size: Size of the vocabulary.
    - embedding dim: Dimension of the dense embedding.
    - input length: Length of input sequences.
g. Next, LSTM layer is added
h. Afterwards, a Dense hidden layer with 16 neurons is added. It will use the ReLU activation function.
i. Another Dense hidden layer with 16 neurons is added, also using the ReLU activation function.
j. Finally, a Dense output layer with the number of neurons being the same as the number of tags in the dataset (i.e one per class) is added. The softmax activation function is used in this layer since the classes are exclusive

## C. Using Bidirectional LSTM (BiLSTM)

The BiLSTM is a type of model used for processing sequences, and it consists of two LSTMs that operate in opposite directions - one from the beginning to the end, and the other from the end to the beginning. This arrangement provides the network with more information, as it can consider both past and future contexts when analyzing the input sequence. This enables the model to better comprehend the sequence and make more precise predictions.




B. Firstly, a sequential model using Sequential() function.

C. Next, an Embedding layer is added which converts each word into a fixed length vector of defined size. Here, there are three parameters:
   - ➔ vocab size: Size of the vocabulary.
   - ➔ embedding dim: Dimension of the dense embedding.
   - ➔ input length: Length of input sequences.

D. Next, a bidirectional layer is added which in turn consists of two layers, one of which is responsible for taking input in forward direction while the other layer is responsible for taking input in backward direction.

E. Afterwards, a Dense hidden layer with 16 neurons is added. It will use the ReLU activation function.

F. Another Dense hidden layer with 16 neurons is added, also using the ReLU activation function.

G. Finally, a Dense output layer with the number of neurons being the same as the number of tags in the dataset (i.e one per class) is added. The softmax activation function is used in this layer to scale the output obtained from the previous layer into probabilities.

## Module 4: Performance Analysis

The following performance metrics were used to analyze the performance of the system:

- Accuracy: It is the fraction of predictions that were correctly made by the model. It is calculated as: Number of correct predictions/Total number of predictions
- Categorical Accuracy: It calculates the fraction of predictions that match one-hot labels. For eg. the target y should be specified as (0,1,0) instead of only 1. It is calculated as: Number of correct predictions/Total number of predictions
- KLDivergence (Kullback-Leibler divergence) : It is calculated as : actual * log(actual / pred), where actual refers to the actual value and pred refers to the predicted value of the target variable. The lower the KL divergence, the better the predicted value.
- Poisson: It is calculated as: pred - actual * log(pred), where actual refers to the actual value and pred refers to the predicted value of the target variable.

The sparse_categorical_crossentropy loss function was used in this case, since the project deals with multi-class classification (where the labels are integers) wherein the user's text was classified to various intents and then appropriate message was displayed.

# Screenshots:

## Sample Code:

## Model.py:

```
import json
import pickle
import numpy as np
import warnings
warnings.filterwarnings("ignore")
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Embedding,
GlobalAveragePooling1D, Bidirectional
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from sklearn.preprocessing import LabelEncoder
from tensorflow.keras import layers



#load the json file
with open('intents.json') as file:
    data = json.load(file)

training_sentences = []
training_labels = []
```

```
labels = []
responses = []

for intent in data['intents']:
    for pattern in intent['patterns']:
        training_sentences.append(pattern)
        training_labels.append(intent['tag'])
    responses.append(intent['responses'])

    if intent['tag'] not in labels:
        labels.append(intent['tag'])

num_classes = len(labels)

lbl_encoder = LabelEncoder()
lbl_encoder.fit(training_labels)
training_labels = lbl_encoder.transform(training_labels)

#text-preprocessing
vocab_size = 1000
embedding_dim = 16
max_len = 20
oov_token = "<OOV>"

tokenizer = Tokenizer(num_words = vocab_size, oov_token = oov_token)
tokenizer.fit_on_texts(training_sentences)
word_index = tokenizer.word_index
sequences = tokenizer.texts_to_sequences(training_sentences)
padded_sequences = pad_sequences(sequences, truncating = 'post', maxlen =
max_len)
```

```python
#model
model = Sequential()
model.add(Embedding(vocab_size, embedding_dim, input_length=max_len))
model.add(GlobalAveragePooling1D())
model.add(Dense(16, activation='relu'))
model.add(Dense(16, activation='relu'))
model.add(Dense(num_classes, activation='softmax'))

model.compile(loss='sparse_categorical_crossentropy',
              optimizer='adam', metrics=['accuracy'])

model.summary()

epochs = 500
history = model.fit(padded_sequences, np.array(training_labels), epochs =
epochs)
# loss, accuracy = model.evaluate(training_sentences)
# print(accuracy)
#save the trained model
model.save('chat-model')

#save the fitted tokenizer
with open('tokenizer.pickle', 'wb') as handle:
    pickle.dump(tokenizer, handle, protocol = pickle.HIGHEST_PROTOCOL)

#save the fitted label encoder
with open('label_encoder.pickle', 'wb') as ecn_file:
    pickle.dump(lbl_encoder, ecn_file, protocol = pickle.HIGHEST_PROTOCOL)
```

**Chat.py:**

```
import json
import os
import numpy as np
import warnings
warnings.filterwarnings("ignore")
from tensorflow import keras
from sklearn.preprocessing import LabelEncoder
import random
import datetime
import webbrowser
import pyttsx3
# from pygame import mixer
# import speech_recognition as sr
import colorama
colorama.init()
from colorama import Fore, Style, Back

import random
import pickle
#speech
from talk import take_command

engine = pyttsx3.init()
voices = engine.getProperty('voices')
```

```
engine.setProperty('voice', voices[1].id)
volume = engine.getProperty('volume')
engine.setProperty('volume', 10.0)
rate = engine.getProperty('rate')

engine.setProperty('rate', rate - 25)
with open('intents.json') as file:
    data = json.load(file)

def chat():
    #load trained model
    model = keras.models.load_model('chat-model')

    #load tokenizer object
    with open('tokenizer.pickle', 'rb') as handle:
        tokenizer = pickle.load(handle)

    #load label encoder object
    with open('label_encoder.pickle', 'rb') as enc:
        lbl_encoder = pickle.load(enc)

    #parameters
    max_len = 20
    while True:
        print(Fore.LIGHTBLUE_EX + 'User: ' + Style.RESET_ALL, end = "")
        inp = input()
        if inp.lower() == 'quit':
            print(Fore.GREEN + 'Bot:' + Style.RESET_ALL, "Take care. See
you soon.")
            break
```

```
        result = model.predict(keras.preprocessing.sequence.pad_sequences(tokenizer.texts_to_sequences([inp]), truncating = 'post', maxlen = max_len))

        tag = lbl_encoder.inverse_transform([np.argmax(result)])

        for i in data['intents']:

            if i['tag'] == tag:

                print(Fore.GREEN + 'Bot:' + Style.RESET_ALL, np.random.choice(i['responses']))



# print(Fore.YELLOW + 'Start talking with Pandora, your Personal Therapeutic AI Assistant. (Type quit to stop talking)' + Style.RESET_ALL)


print("Hi there! Can you tell if you would like to chat with me or talk to me ?")

val=input()


if val.lower()=='chat':

    chat()

elif val.lower()=='talk':

    #load trained model

    model = keras.models.load_model('chat-model')


    #load tokenizer object

    with open('tokenizer.pickle', 'rb') as handle:

        tokenizer = pickle.load(handle)


    #load label encoder object

    with open('label_encoder.pickle', 'rb') as enc:

        lbl_encoder = pickle.load(enc)
```

```
    #parameters
    max_len = 20
    while True:
        print(Fore.LIGHTBLUE_EX + 'Listening: ' + Style.RESET_ALL, end = "")
        inp = take_command()
        if inp.lower() == 'quit':
            print(Fore.GREEN + 'Cutie Bot:' + Style.RESET_ALL, "Take care. See you soon.")
            break
        result = model.predict(keras.preprocessing.sequence.pad_sequences(tokenizer.texts_to_sequences([inp]), truncating = 'post', maxlen = max_len))
        tag = lbl_encoder.inverse_transform([np.argmax(result)])
        for i in data['intents']:
            if i['tag'] == tag:
                print(Fore.GREEN + 'Pandora:' + Style.RESET_ALL, np.random.choice(i['responses']))
```

**Sample output:**

**Running model.py:**

```
PS W:\WinterSem 2022-2023\NLP\Updated J Comp\NLP> python model.py
2023-04-06 10:21:10.514061: I tensorflow/core/platform/cpu_feature_guard.cc:193] This TensorFlow binary is optimized with oneAPI Deep
Neural Network Library (oneDNN) to use the following CPU instructions in performance-critical operations:  AVX AVX2
To enable them in other operations, rebuild TensorFlow with the appropriate compiler flags.
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 20, 16)            16000

 global_average_pooling1d (G  (None, 16)               0
 lobalAveragePooling1D)

 dense (Dense)               (None, 16)                272

 dense_1 (Dense)             (None, 16)                272

 dense_2 (Dense)             (None, 81)                1377

=================================================================
Total params: 17,921
Trainable params: 17,921
Non-trainable params: 0
_________________________________________________________________
Epoch 1/500
8/8 [==============================] - 1s 3ms/step - loss: 4.3952 - accuracy: 0.0086
Epoch 2/500
8/8 [==============================] - 0s 3ms/step - loss: 4.3896 - accuracy: 0.0302
Epoch 3/500
8/8 [==============================] - 0s 3ms/step - loss: 4.3852 - accuracy: 0.0259
Epoch 4/500
8/8 [==============================] - 0s 3ms/step - loss: 4.3801 - accuracy: 0.0259
Epoch 5/500
```

## Running chat.py:

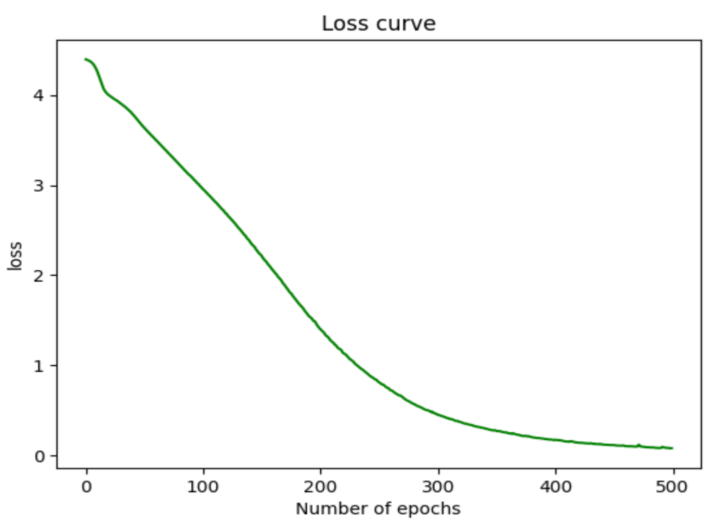
```
PS W:\WinterSem 2022-2023\NLP\Updated J Comp\NLP> python chat.py
Hi there! Can you tell if you would like to chat with me or talk to me ?
Chat
2023-04-06 10:36:54.985415: I tensorflow/core/platform/cpu_feature_guard.cc:193] This TensorFlow binary is optimized with oneAPI Deep
Neural Network Library (oneDNN) to use the following CPU instructions in performance-critical operations:  AVX AVX2
To enable them in other operations, rebuild TensorFlow with the appropriate compiler flags.
User: Hello there
1/1 [==============================] - 0s 89ms/step
Bot: Hello there. Tell me how are you feeling today?
User: I'm feeling good.
1/1 [==============================] - 0s 23ms/step
Bot: Why do you think you feel this way?
User: I got selected for job.
1/1 [==============================] - 0s 22ms/step
Bot: That's geat to hear. I'm glad you're feeling this way.
User: Thank you.
1/1 [==============================] - 0s 19ms/step
Bot: Happy to help!
```

## Recurrent Neural Network (RNN)

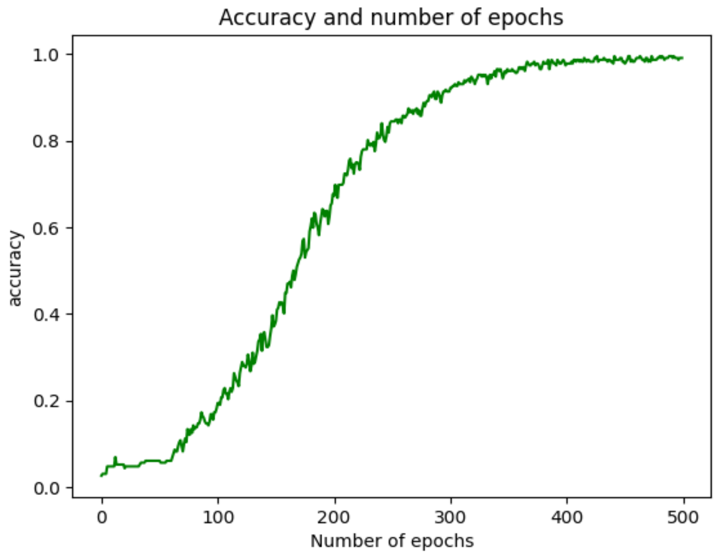
```
model = Sequential()

model.add(Embedding(vocab_size, embedding_dim, input_length=max_len))

model.add(GlobalAveragePooling1D())

model.add(Dense(16, activation='relu'))

model.add(Dense(16, activation='relu'))
```

```
model.add(Dense(num_classes, activation='softmax'))

model.compile(loss='sparse_categorical_crossentropy',
              optimizer='adam', metrics=['accuracy'])

model.summary()
```

## Loss curve:



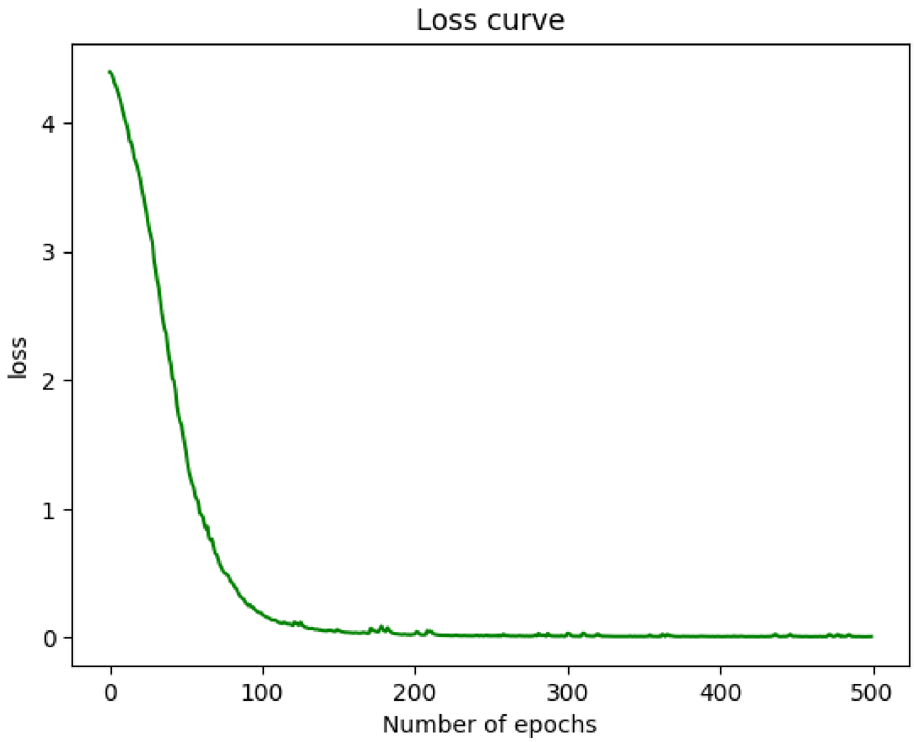

## Accuracy and Number of epochs:



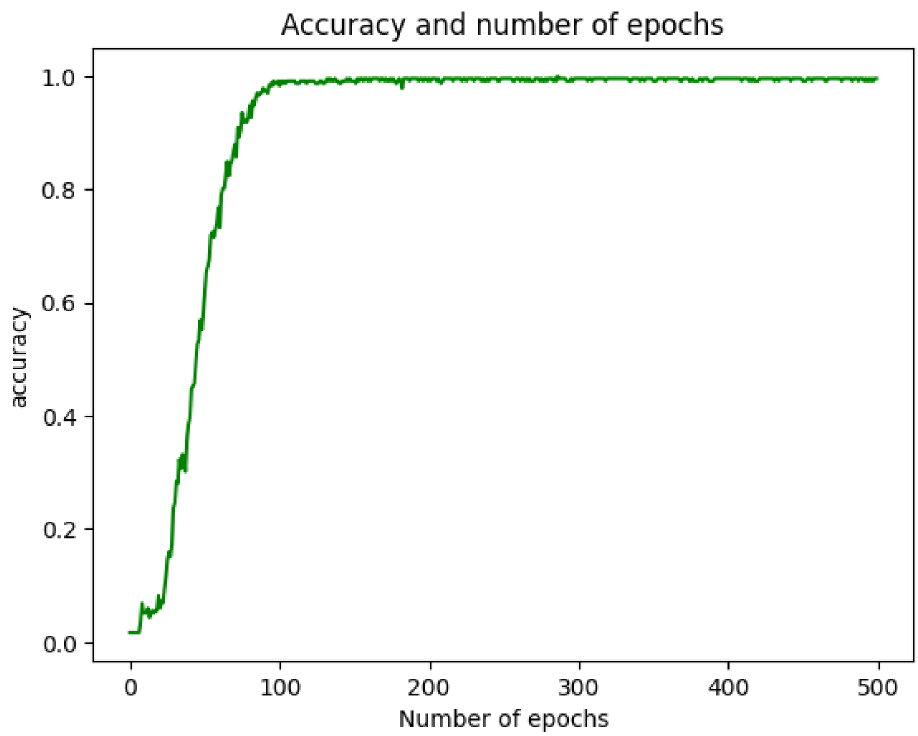

## Long Short-Term Memory (LSTM)

```
model = Sequential()
model.add(Embedding(vocab_size, embedding_dim, input_length=max_len))
model.add(layers.LSTM(128))
model.add(Dense(16, activation='relu'))
model.add(Dense(16, activation='relu'))
model.add(Dense(num_classes, activation='softmax'))
```

## Loss curve:



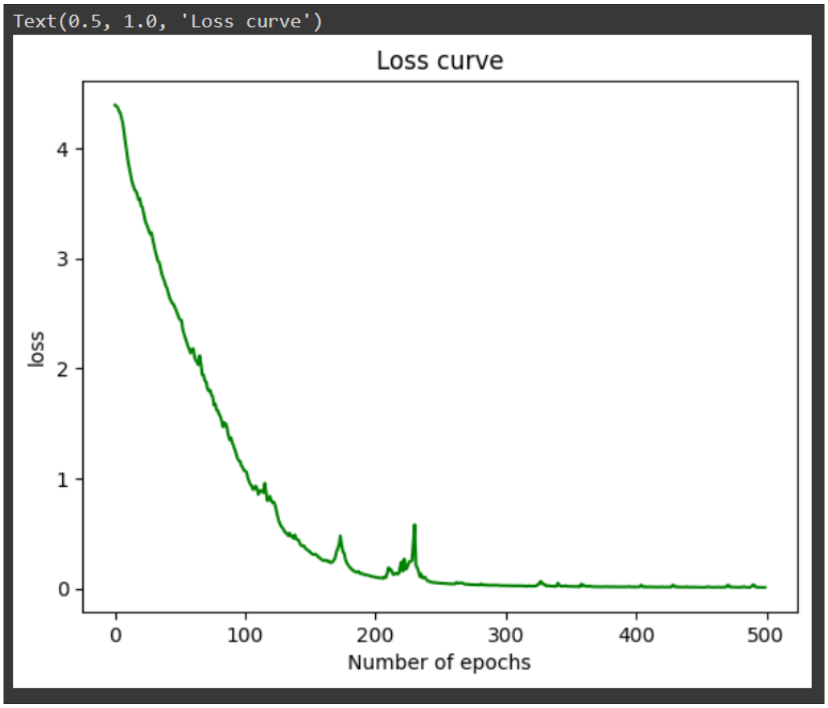

**Accuracy and number of epochs :**



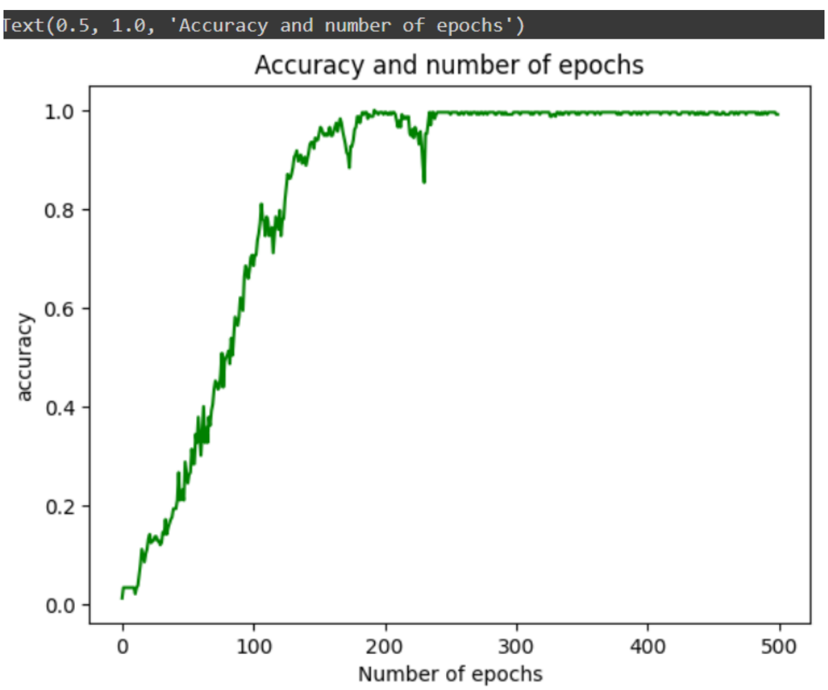

## Bidirectional Long Short-Term Memory (BiLSTM)

```
model = Sequential()

model.add(Embedding(vocab_size, embedding_dim, input_length=max_len))

model.add(Bidirectional(tf.keras.layers.LSTM(64))),

model.add(Dense(16, activation='relu'))

model.add(Dense(16, activation='relu'))

model.add(Dense(num_classes, activation='softmax'))
```

## Loss curve:




## Accuracy and Number of epochs:

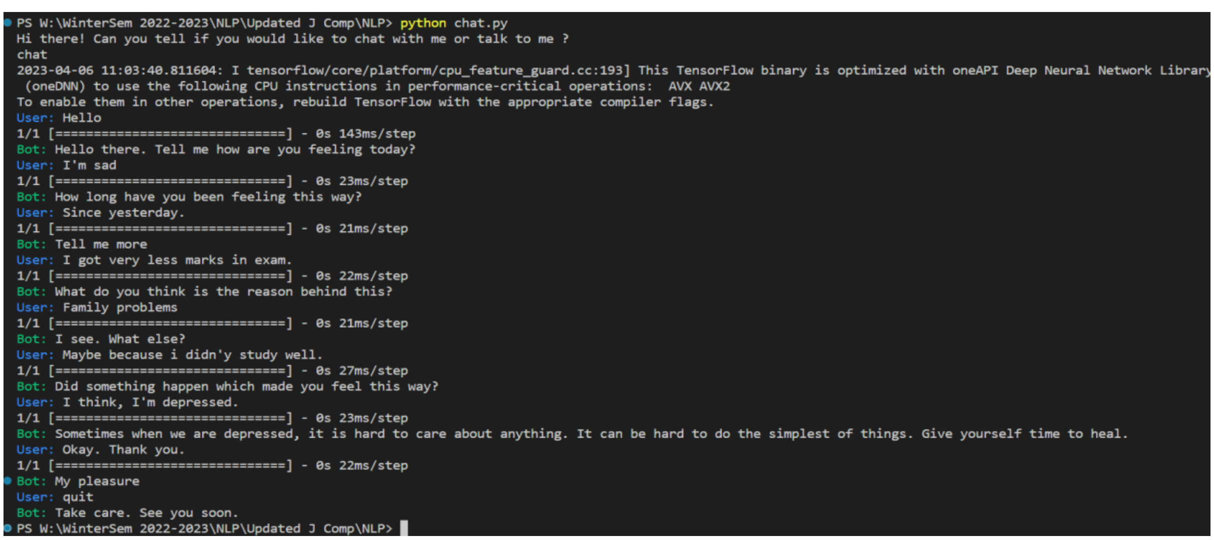


## Results and Discussion :

This project takes on the job of a counselor or therapist whose main purpose is to spread awareness about mental health and major depressive disorder and can be accessed by any individual. The following table displays the comparative results of the performance metrics of all the models implemented in our project, and the accuracy of the LSTM model is notably the highest .

| Model implemented | Sparse Categorical Cross Entropy loss function | Poisson | K L Divergence | Accuracy obtained |
|---|---|---|---|---|
| Recurrent Neural Network (RNN) | 0.235 | 618.02 | 1148.07 | 96.5 % |
| Long Short Term Memory (LSTM) Model | 0.008 | 650.17 | 1203.88 | 99.5 % |
| Bidirectional Long Short Term Memory (BiLSTM) Model | 0.011 | 649.46 | 1209.1 | 99.1 % |

## Sample Output Chat and Explanation :



```
PS W:\WinterSem 2022-2023\NLP\Updated J Comp\NLP> python chat.py
Hi there! Can you tell if you would like to chat with me or talk to me ?
chat
2023-04-06 11:03:40.811604: I tensorflow/core/platform/cpu_feature_guard.cc:193] This TensorFlow binary is optimized with oneAPI Deep Neural Network Library
 (oneDNN) to use the following CPU instructions in performance-critical operations:  AVX AVX2
To enable them in other operations, rebuild TensorFlow with the appropriate compiler flags.
User: Hello
1/1 [==============================] - 0s 143ms/step
Bot: Hello there. Tell me how are you feeling today?
User: I'm sad
1/1 [==============================] - 0s 23ms/step
Bot: How long have you been feeling this way?
User: Since yesterday.
1/1 [==============================] - 0s 21ms/step
Bot: Tell me more
User: I got very less marks in exam.
1/1 [==============================] - 0s 22ms/step
Bot: What do you think is the reason behind this?
User: Family problems
1/1 [==============================] - 0s 21ms/step
Bot: I see. What else?
User: Maybe because i didn'y study well.
1/1 [==============================] - 0s 27ms/step
Bot: Did something happen which made you feel this way?
User: I think, I'm depressed.
1/1 [==============================] - 0s 23ms/step
Bot: Sometimes when we are depressed, it is hard to care about anything. It can be hard to do the simplest of things. Give yourself time to heal.
User: Okay. Thank you.
1/1 [==============================] - 0s 22ms/step
Bot: My pleasure
User: quit
Bot: Take care. See you soon.
PS W:\WinterSem 2022-2023\NLP\Updated J Comp\NLP>
```

The conversation between the user and the bot demonstrates the bot's ability to comprehend the user's intent and provide supportive responses. After exchanging greetings, the user expresses their sadness due to poor exam results. The bot responds by asking for the reasons behind the sadness and listens attentively as the user shares their struggles with family problems, lack of preparation, and depression. The bot provides empathetic feedback, acknowledging that depression can make it difficult to care about anything and advises the user to take some time to heal. Overall, the conversation ends with the user feeling better due to the supportive conversation provided by the bot.

## Conclusion:

In conclusion, the development of a therapeutic AI assistant has the potential to significantly improve mental health support by providing personalized and accessible care to individuals in need. By using natural language processing, machine learning, and other technologies, the AI assistant can provide effective support for a range of mental health issues. Additionally, features such as a mood tracker and integration of Cognitive Behavioral Therapy can further enhance the quality of care provided by the assistant. As technology continues to evolve, the development of a therapeutic AI assistant represents an exciting opportunity to revolutionize mental health care and provide much-needed support to those struggling with mental health issues.

In summary, chatbots for mental healthcare are still in their early stages and require further research and development to ensure effective treatment of patients. While they can be a useful resource for patients seeking initial help, they cannot replace the importance of human connection and traditional therapy channels provided by professional therapists. This, AI assistant, is designed to complement the work of mental healthcare professionals and fill gaps in treatment rather than replacing them altogether. The collaboration between this system and mental healthcare professionals can provide patients with improved care and support.

## Future Scope

- **To improve the dataset:** To improve the quality of the machine learning model, more data related to mental health and therapy can be collected by scraping forums and online communities.
- **To design a user interface:** An interactive interface for the user to communicate with the AI assistant, could be developed using either a web or Android application.

- **To implement CBT:** Cognitive Behavioral Therapy (CBT) can be integrated into bot's functionalities to help users identify and change negative thought patterns, thereby increasing their confidence level and the will to live.
- **To develop a mood tracker:** A feature to record a person's mood regularly can also be created, which would allow the users to track patterns and variations in their mood over time, which can be helpful for improving mental health.

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