A secured self-learning counselling system leveraging RNN

by

Rifat Sarker Aoyon
22341043
Yamin Ara
19301187
Arafat Rahman
19101354
Easin Mahmud
19101346
Ibrahim Lokman
19101372

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Declaration

It is hereby declared that

1. The thesis submitted is my/our own original work while completing degree at Brac University.

2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.

4. We have acknowledged all main sources of help.

Student's Full Name & Signature:

Rifat Sarker Aoyon

22341043

Yamin

Yamin Ara

19301187

Arafat Rahman

Arafat Rahman

19101354

Easin

Easin Mahmud

19101346

Ibrahim Lokman

Ibrahim Lokman

19101372

Approval

The thesis/project titled ”A secured self-learning counselling system leveraging RNN” submitted by

1. Rifat Sarker Aoyon (22341043)
2. Yamin Ara (19301187)
3. Arafat Rahman (19101354)
4. Easin Mahmud (19101346)
5. Ibrahim Lokmam (19101372)

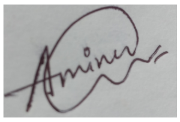
Examining Committee:

Supervisor:
(Member)

Md. Tanzim Reza

Lecturer
Department of Computer Science and Engineering
Brac University

Co-Supervisor:
(Member)



Aminul Huq

Lecturer
Department of Computer Science and Engineering
Brac University

Program Coordinator:
(Member)

Md. Golam Rabiul Alam

Professor
Department of Computer Science and Engineering
Brac University

Head of Department:
(Chair)

Sadia Hamid Kazi, PhD

Chairperson and Associate Professor
Department of Computer Science and Engineering
Brac University

Abstract

Chatbots are virtual assistants providing round-the-clock service across many sectors globally. It helps manage human workforce scarcity. As such, the need for mental health care services has been on the rise. Currently, the demand exceeds the availability of such services. Moreover, in many parts of the world, mental health care is still inaccessible due to various socio-economic reasons. In this research, we propose a Chatbot to aid in providing mental health care services that is accessible from anywhere in the world. Our model will be capable of providing accurate psychological health care as well as ensuring the privacy of data that users share with the Chatbot. We have used RNN to train the model of this Chatbot. Many users' conversations can be used to train this Chatbot easily as we have followed the RNN algorithm in a way that allows us to train large quantity of data in a comparatively less powerful machine. However, it is imperative to stress that these conversations are solely used for training the model. No one except users will be aware of the conversations with the Chatbot. Moreover, we plan to implement self-learning technology to combat the insufficiency of data necessary for training our model. The more it is used, the better it will get, learning from the user's responses.

Keywords: Chatbot, Mental health Care, ensuring the privacy of data, self-learning technology, RNN.

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Chapter 1

Introduction

"Unexpressed emotions will never die. They are buried alive and will come forth later in uglier ways. " -Sigmund Freud [1]. We interact with people every day, but how much of it do we spend inquiring about their mental health and how often do they respond with the truth? In the US, approximately 1 in 4 people above the age of 18 are diagnosed with one or more mental health problems yearly [2]. Only 19.2% of them seek any sort of help [3]. Often because of social scrutiny, confidentiality issues, lack of resources, or finances people fail to get the help they need [4]. Lack of action taken to improve their mental health only worsens the cases' overall life. WHO studies show a correlation between poor mental health and a decrease in Gross Domestic Product. These concerns can be resolved using a mental healthcare Chatbot that eliminates the need for expensive therapy sessions as well as brings the input from the best therapists and counselors, which is especially difficult to find in underdeveloped nations, at the tip of their fingers inside the privacy of their homes. Most Chatbots currently available are only able to make mediocre diagnoses, like the 7cups website Chatbot, which asks questions to make a diagnosis [5] and then connects users to human listeners or paid counselors, of which only very few are able to effectively aid the users with their problems. Another example would be the Woebot, it uses Cognitive Behavior Therapy using natural language processing to recognize and help users identify and change dysfunctional behaviors [6] but these do not protect the user data well. This brings us to our AI-driven Chatbot. Using data from mental healthcare professionals and patients, this will be a self-learning Chatbot integrated with RNN which keeps sensitive data of users private so that they can use the Chatbot with zero concerns of privacy breaches. This self-learning Chatbot will be utility-based; therefore, it will be able to pick up user linguistic cues accurately and provide relevant feedback.

1.1 Research Objective

Even though mental health and physical health are equally important, most tend to neglect taking care of their mental health. This scenario is not only visible in first-world countries but also in third-world countries. For this reason, our research objective is to make a Chatbot that can provide mental healthcare solutions like a professional psychologist. Initially, we plan to make this Chatbot in such a way so that huge amount of data can be trained easily in a comparatively less powerful machine to enable a large number of users to easily share their data with the Chatbot.

After that, we have another objective, which is to ensure the privacy of the users. By using these two objectives mentioned above, we will create a powerful Chatbot capable of providing psychological counseling equivalent to a professional. However, in order to establish this Chatbot, we need a large amount of data, which is almost impossible to manage. Hence, another objective of ours is to add a self-learning system to this Chatbot that can learn continuously by conversing with the users. This way, we plan to build an outstanding Chatbot even after lacking a large amount of data.

1.2 Problem Statement

Today, many mental healthcare Chatbots are available. People are benefiting in many ways by utilizing these conversational agents. Even after having many advantages, some drawbacks can be noticed in these Chatbots. One of the prime issues is the inability to provide sufficient accuracy. For instance, we can mention Woebot [7]. This particular Chatbot has trouble maintaining a properly accurate conversation. That is why, sometimes, users will not get proper solutions to their problems and may become further distressed because of getting inaccurate answers from this Chatbot. Another noticeable concern is the lack of privacy maintenance in these Chatbots. Woebot sometimes shares the user's personal data with third parties [8]. Therefore, people hesitate to reveal any important information to the Chatbot and in doing so; they do not talk freely, leaving out information that could save their lives. This scenario is not just visible in Woebot but also in other psychological Chatbots that collect the user's conversational data. For this reason, we propose a Chatbot that is able to provide sufficient accuracy alongside ensuring the privacy of the user's conversation. That means, except for the user, no one will be able to know about the conversation with the Chatbot. Even the person who has made this Chatbot will not be able to see this conversational data. However, another particular problem persists in the path to making this Chatbot; managing a huge amount of conversational data which is required for making an efficient Chatbot that has the ability to provide proper mental health counseling. This enormous amount of conversational data is impossible to collect centrally in real life thus causing a shortage of data. In order to mitigate this problem of data shortage, we will add a self-learning feature to this Chatbot. This will utilize the user's conversation for training the Chatbot. Therefore, by constantly interacting with users, the Chatbot will improve day by day. We have implemented RNN to train the dataset while maintaining the privacy of the users' conversations. However, a powerful computer is necessary to train the large dataset. By following our proposed methods, using a large quantity of data, the Chatbot can be trained in a comparatively less powerful machine.

Chapter 2

Literature Review

2.1 Psychiatric Counseling Using chatbot

A Chatbot is a type of conversational user interface with the ability of giving responses to human queries. Similar to its usage in many sectors, Chatbots are also present in the sector of mental health care. These Chatbots fulfill the need of giving counseling. In spite of mental health and physical health having equal importance, people are not seeking treatment for mental ailments. Two primary reasons are fear and shame [9]. This scenario is mainly present in third-world countries, where mental health topics are considered taboo. Due to this outlook of the society, a person with possible psychological problems is disinclined to contact a psychologist for proper diagnosis and treatment. That is why, researchers are inventing Chatbots based on artificial intelligence, machine learning, or deep learning that can efficiently provide mental health therapy through conversation remotely. Currently, many Chatbots are available that ensure privacy and have the ability to give responses like professional psychologists [10]. The comprehensive usage of smartphones and availability of internet connection has made these technologies accessible to many users around the world. These artificial conversational agents can be a solution for patients who need psychological help by providing a suitable platform for users to securely express their mental health concerns and receive treatment.

2.2 Emotion Recognition Methods

To give solutions to psychological problems, the initial task is to recognize the emotions of the users from conversational data. Various algorithms are available that can recognize emotions from text conversation [11]. Some of these algorithms are as follows:

- Statistical methods
- Knowledge-based techniques
- Hybrid approaches, etc.

2.2.1 Statistical methods

In statistical method approach, supervised machine learning algorithms is used. Large datasets of annotated data is used to training the model. The deep learning algorithm is the most used here as it has the capability of providing comparatively more accuracy than some other algorithms. Thus, we can notice its success in emotion recognition.

2.2.2 Knowledge-based techniques

In knowledge-based techniques, we can see the implementation of domain knowledge and the semantic and syntactic characteristics of language, which can identify the proper emotion. There are two groups available in knowledge-based techniques, which are dictionary-based and corpus-based approaches. Dictionary-based approaches utilize the root meaning of a word and search for its similar and opposite meanings from the dictionary in order to complete the emotion detection purpose. Meanwhile, Corpus-based approaches also begin their operation with a root catalog of opinion or emotional words but the expanding task of its database is completed by discovering other words with context-specific characteristics in a large corpus.

2.2.3 Hybrid approaches

The hybrid approach is an alliance of the two methods, knowledge-based techniques and statistical methods. Therefore, the benefits of both processes are present here, which makes it helpful for providing outstanding performance in emotion recognition. However, even though it has so many phenomenal facilities, sometimes it might create problems during classification due to computational complexity.

2.3 Related Datasets

2.3.1 Multimodal EmotionLines Dataset (MELD)

Multimodal EmotionLines Dataset (MELD) is an unique dataset for training models for extracting emotion from conversational data of the users [12]. Along with textual conversational data, there is some data available in the dataset that can be beneficial for recognizing emotions from audio and visual modalities. There are more than 1400 dialogues and 13000 utterances in MELD, which was collected from a TV series called "Friends". In this dataset, emotion has been divided into seven categories, which can be found in every utterance.

2.3.2 DailyDialog

This DailyDialog dataset is based on our daily conversation [13]. If we utilize this dataset, we can expect to get a realistic reply from a Chatbot. This dataset has ten categories, which makes it unique from domain-specific datasets. This dataset has categorized emotions in some labels in order to maintain high quality. That is why it will be easier for a person to find out specific emotions from the conversation.

2.3.3 EmoryNLP

EmoryNLP is another amazing dataset that can be used to train models for detecting emotions from text [14]. There are 97 episodes, 897 scenes, and 12,606 utterances visible in the EmoryNLP dataset. In this dataset, there are seven types of emotions that were created based on the feeling wheel of Willcox [15]. Every utterance is annotated with one of the seven emotions.

2.3.4 EmoContext

The EmoContext dataset is one kind of dataset that is helpful for training models to find out emotions from text [16]. This dataset comprises 30160 dialogues and 2 evaluation data sets named Test1 and Test2. There are 2755 dialogues visible in Test 1, and on the other hand, 5509 dialogues are visible in Test 2. In total, 311 teams have assisted in making this dataset successful.

2.3.5 SEMAINE

Utilizing SEMAINE (an audiovisual dataset) is a great initiative to recognize emotions from conversations [17]. There were 150 people involved in this project for making this database. These 150 people created 959 conversations, each being around 5 minutes long. These recordings have been annotated many times. Every clip is traced in five dimensions and divided into 27 groups.

2.4 RNN

Recurrent Neural Network(RNN) a one kind of neural network where every current node is connected with the previous node and for this reason, RNN is widely used for sentence generation [18]. This algorithm can also be used in the sector of speech generation. There are some hidden layers in the RNN algorithm but as the value of the current node depends on the previous node in the RNN, it is possible to track the information of all the nodes in an RNN. There are mainly four types of RNN available. First one is the "one to one" RNN that provides single output for single input. Second type of RNN named "one-to-many" RNN delivers multiple outputs for a single input. The third type is called "many to one" that works by giving a single output for multiple inputs. The last type of RNN takes multiple inputs at a time and delivers all the outputs for these inputs together. This type of RNN is called "many-to-many" RNN.

2.5 Other Mental Health Care Chatbots

2.5.1 Joyable

Joyable is an outstanding mental healthcare Chatbot based on the principles of Cognitive Behavioural Therapy [19]. Initially, in order to create a profile of a user, this particular user has to answer some questions [20]. This question-answer task is helpful for identifying the user's mental health condition. Moreover, this Chatbot connects the users with a real-time assistant who helps the users by providing sufficient guidelines [21].

2.5.2 Moodnotes

Moodnotes is a mental health care virtual assistant which helps users by giving some psychological suggestions which create positivity in the user [22]. This virtual assistant asks users particular questions to recognize the user's mental health stage. This application works based on the techniques of CBT [23]. Thriveport and Ustwo have worked together to make this psychological counseling app by taking help from the CBT experts.

2.5.3 Wysa

Wysa is an AI-enabled mental health care Chatbot that is capable of providing mental healthcare by ensuring the privacy of the user's conversations [24]. Whenever a user tells Wysa about his or her problems, Wysa asks some questions to understand the situation of the user properly. Based on the responses of the user, Wysa makes a toolkit that is very beneficial for improving the user's mental health.

2.5.4 WoeBot

WoeBot is an automated mental health counseling Chatbot that was created in 2017 by a group of researchers at Stanford University [25]. These researchers have invented this unique innovation by utilizing the technology of natural language processing. The Woebot organizes daily ten-minute conversations with users in order to find out the stage of the user's mental illness [26]. WoeBot also provides some exercises for users based on the conversation to solve the problems of mental health.

2.6 Related Works

In this paper [27], the author proposed a Chatbot model for emotion recognition. This Chatbot is capable of recognizing emotions from various types of data, like audio, video, images, and text messages. In order to recognize emotions, the initial task is to understand the sentence, which is a great challenge as sentence expression levels vary from person to person. To deal with this challenge, the writer utilizes the Sense-based morpheme-embedding model. The author creates a division of emotions based on Plutchik's wheel of emotions. In order to train models about emotion recognition, the author collects data from various sources, like dramas and radio programs, which contain emotional dialogues. The author utilizes these kinds of conversations in order to train the model accurately with the help of RNN, LSTM, and GRU algorithms. Another unique feature is the ability to keep track of changing emotions. The final task is giving responses to users' messages, which is done based on the Pointer network-based dialogue response generation model in this research. To train the Chatbot to provide responses, the author has focused on gender, age, and the ethical code of humans. Finally, the author expressed his desire to include

Chatbots for adolescent game addiction cases.

In this paper [28], the author introduces a novel Chatbot for students who are suffering from depression. According to the author, one of the most efficient methods for reducing anxiety and depression is by getting encouragement from other people. Sometimes, people are afraid of sharing their confidential information with others, which prompted the author to make a Chatbot in order to give enough confidence to share any kind of sensitive issue. In this research, the author has classified depression levels into eight classes. According to the author, without joy and happy levels, the remaining six models are considered negative and only these two levels are mentioned as positive. The author has utilized the ISEAR dataset to complete the task of detecting emotion from the text. After data collection, they have focused on training and testing the model. For proper training and testing, they created three divisions of training and testing segments. The initial part of training and testing is tokenization, which is done by Punkt Sentence Tokenizer. After completing the task of tokenization, the author has given focus to forming word vectors using unsupervised learning. Next, the author did the task of embedding the words. After that, one of the most significant tasks started by the author is, "Classification of the Emotions from Text," which is done by CNN, RNN, and HAN. In this research, the utilization of CNN is visible in order to recognize the mental state of users, and the percentage of positivity and negativity is measured based on CNN and RNN. Eventually, the author set a feature in the Chatbot that is able to give suggestions for mental health treatment based on emotional level.

In this paper [29], the author has mentioned SERMO, which is a mobile application-based Chatbot that uses CBT to help deal with mental health ailments. Denecke, Vaaheesan, and Arulnathan saw the current limitations of mental health facilities as well as existing Chatbots with limited conversation and language support only available in English, and decided to develop this Chatbot in their native German. This model analyzes input from the user to identify emotions using a syntactic and semantic approach contrary to existing decision-tree integrated models. They worked together with psychologists, patients, and existing literature to better understand the requirements of the Chatbot. SERMO uses the Syn.Bot framework, OSCOVA, and SIML interpreter to process input, as well as Xamari.Forms and SQLite to store data. In ABC theory, dialogue is used to converse with and aid the user. Writing errors are fixed using a fuzzy matching method. A usability test was carried out using 21 individuals from different backgrounds using UEQ, which found shortcomings in system stability and variation of responses of the bot. This article further discusses the usage of CBT and a few conversational agents that have unique features like mood trackers and movement trackers via mobile accelerometer. Moreover, the issues with lexicon-based models are addressed where one word can have different meanings in different situations, and so an ML model like Naive Bayes or SVM with its supervised learning is a superior judge of context. They studied prominent medical documents and identified challenges with sentiments and emotional analysis. Lastly, it was noted that privacy concerns have to be addressed to protect user data in order to make this application publicly available, along with improvements in conversational diversity.

In this conference paper [30], a framework in conjunction with Blockchain and machine learning is discussed alongside encryption technologies in its application to federated learning to accelerate evidence-based medical science while protecting the patient's data in healthcare systems. Therefore, use of Blockchain will be greatly beneficial. This article also ruminates on how to encourage users to share data using a reward mechanism, but this does not take the quality of data into account. The paper also introduces us to Google's FA protocol, which keeps user data private but is subject to model poisoning and centralization. Blockchain can overcome this problem by creating blocks that users can view and aggregate themselves while BAFFLE protocol can combat model poisoning. However, this poses a cost-effective use case for a public blockchain. The expense is justified by the intent to make a free common good for all. Kang et al. use RONI or FoolsGold to clean up model poisoning. The authors enlighten us about Substra, ab FL, and the blockchain framework, which is used in private healthcare. In the FA model, updates are automatically made locally to save time. Security is maintained by providing each user with only the bare minimum information so that training sets and their parameters remain unknown. The disadvantage of such high technology is that the devices needed to run the algorithms may not be widely available. Moreover, the paper discusses the difficulty of finding good trainable labeled datasets without human intervention. Furthermore, the research focuses on various systematic and social biases that can affect ML results and how they could be overcome using FL, which will improve privacy and diversity. The authors emphasize that future innovations using federated ML for better collaborative research on patient data, Blockchain to decentralize, and advanced cryptography for privacy together will solve many problems in the healthcare industry that one of them alone cannot.

In this paper [31], the authors used a genetic algorithm designed using AI to create a partially automated diagnosis system to improve the accuracy of mental disorder diagnosis. It extracts data from user-input descriptions of symptoms using BPEL and matches it with a keyword database present in its system to generate a population of all possible mental illnesses, sorted according to most to least probable, without bias. The final choice made by an intelligent classifier or professional. In this algorithm, the fitness function is based on the frequency of keyword appearance, and the one with a lower fitness value actually has a better outcome than the one with a higher value. The model has the flexibility to improve its efficiency with time and performs better than the k-means algorithm. This model can be used for various applications that require cost-efficient and fast data collection procedures.

In this paper [32], the author has introduced a Chatbot that has the ability to give psychological therapy by utilizing the technology of texting, voice messaging, and video calls. This Chatbot was created based on natural language processing (NLP) and collected data from a variety of sources by using mobile device features. The author has implemented Dialogflow for giving responses to text messages. In the sector of giving responses from video messages, the author has included a facial emotion recognition technology named MobileNetV2 in order to predict the emotions of the users. By getting help from the NLP algorithm, this Chatbot analyzes the mental health condition of the users based on the text, voice, and video messages that are sent by the users.

In this paper [33], the author has introduced a method for detecting depression while ensuring the privacy of the users using federated learning. The author has displayed a comparison between federated learning frameworks and other cooperative learning frameworks in order to reveal the higher accuracy of federated learning than other cooperative learning frameworks. In federated learning, there is no need to centralize data in order to complete the task of training machine-learning models. In place of centralizing data, it puts all the trained data together, which is optimized by using federated averaging technology successively to give chance to data sharing. In this research, the author has taken advantage of smartphones to complete the task of collecting data. The author has created a virtual keyboard for mobile phones and compared the keystroke habits of normal and depressed people, as well as their typing speeds. This difference has been used to make a dataset for training a model. Each user has to spend an initial 80% period in order to train and spend the remaining 20% to measure the accuracy. After completing the creation of the dataset, the author makes 2 divisions of this dataset, which are IID and Non-IID. When the author finished this experiment, he found that the amount of accuracy in federated learning with IID data is around 10 to 15 percent better than the local training method. In the sector Non -IID, the quantity of exactness is decreased by up to 13 percent. To conclude, the use of federated learning for fulfilling the purpose of ensuring data privacy is acceptable. Finally, the author talks about his future plan to remove the dominance of non-IID data from the model.

In this paper [34], the author has introduced a tool for adults that is capable of screening and predicting mental disorders based on fuzzy-logic. The author showed the modeling process based on FL of complex decision-making in adults. In order to show that the author has managed screening for seven mentally disabled people and finally found out the best one by implementing Fuzzy Logic. There are three reasons that make this research unique. These are in harmony with real-life data, the implementation of the supreme method for screening, and the proper identification of every response. According to the author, this research can be beneficial for doctors to find out the probability of being ill. Moreover, it can be helpful to the people of developing countries through utilizing it as a supplement to the insights of general practitioners. The author has implemented a genetic algorithm in order to train this model. Experience achieved by the controller is beneficial for further developing the functions of this model.

In this paper [35], an approach using deep language models was investigated for tackling the diagnosis process of mental health conditions like anxiety and depression. Using speech data from over 11.000 patients, a transfer-learning NLP model is used for comparison of conditional performance measurement. A model variability measure shows that word-based cues for the conditions are far more prominent for depression than for the others. LSTM technology and ULMFiT influenced NLP model creation. This model performs well when both conditions are present or absent together. The studies that were done by these researchers show high comorbidity and positive data skewness of severity in the conditions, which persist even after adjustments are made for the skew. Hence, the results suggest that the correlation between the two behavioral health conditions needs to be taken into account when building screening applications.

This study [36] aimed to analyze and identify depression through people's blog posts on the internet. As the article states, depression is a mental illness that causes people to feel sadness and fills them with negative emotions. If this illness is not treated, patients may take the wrong steps, which may be tragic. To prevent tragedies, there are many questionnaires for self-diagnosis of depression. According to the author, however, most of these questionnaires are dull, unnecessarily long, and unclear. For this reason, the author wants to utilize Latent Dirichlet Allocation (LDA) to discover people with depression through social media platforms. As the author states, depressed people behave quite differently on social media platforms than healthy people, and these behaviors can be easily identified. Moreover, the author suggested using SentiWordNet to know the severity of one's depression. Thus, the author received an 80 percent success rate in their experiment for detecting depression from real datasets collected from online. Eventually, the author states that in the future they can discover the effectiveness of their treatment by observing people with depression as their emotions change in rehabilitation.

In this paper [37], the author has introduced a deep learning algorithm that can predict the future diagnosis of depression. This deep learning model is a bidirectional model, which is capable of performing bidirectional representation learning on multimodal electronic health records. As well as, the author has proved this algorithm's ability to sum five heterogeneous and high-dimensional data sources from the Electronic Health Record. After completing the task of aggregation of this data, the job of processing this data begins. In order to outperform the current state-of-the-art, the author implemented two stages, named pre-training and fine-tuning, on the data of the Electronic Health Record. According to the author, because of utilizing these two stages, high performance can be noticed in the sector of recognizing accurate levels of depression. The author has also shown that utilizing this kind of method on electronic health record data can be a great solution in order to erase the problem of data limitation.

In this paper [38], the author has shown a unique method based on deep learning algorithms to diagnose depression from facial appearance and dynamics. For the purpose of training the model, two datasets, which are AVEC2013 and AVEC2014 were utilized. The author successfully trained the model using DCNN. Two kinds of DCNN were designed to train the model properly. These are appearance DCNN and dynamics DCNN. In this research, the author improved the performance by attaching these two kinds of DCNN together. Only video data were used except when using audio cues. As per the claim of the author, even after using just visual data, this method is more capable than many other visual-based approaches in the sector of predicting depression, where other methods have used both audio and video data.

In this paper [39], the author has shown a treatment process for predicting social anxiety based on conversations via email. To train the model properly, data of 69 patients were used. The author claims that conversation datasets can play a significant role in the field of giving treatment for social anxiety. The paper focuses on five perspectives to predict anxiety from the email, which are the following:

- Basic mailing behavior
- Usage of words
- Style of writing
- Sentiment
- topic.

After collecting this data from everyone's email, the author aggregated it by utilizing the machine-learning algorithm. This is because the amount of data is insufficient. Hence, the author faced difficulty in attempting to generalize the model. Despite this, the author claims that this model can play an outstanding role in predicting anxiety from electronic conversations.
In this paper [40], the author has introduced an incredible conversational agent with the ability to provide perinatal mental healthcare to maternal women. The author has invented this Chatbot based on the supervised machine learning method by analyzing the 31 characteristics of 223 samples. This model is trained to recognize some perinatal mental health problems such as depression, anxiety, or hypomania. The author preferred to utilize SVM because of its outstanding accuracy and because SVM does not have any great issues for training the model like CNN. Due to the presence of some problems in CNN, the author does not use CNN to train the model even though it delivers more accuracy than SVM. By utilizing this Chatbot, it is possible to observe the condition of perinatal women in real time. This method of mental healthcare for maternal women can play a more significant role than most other traditional methods due to having sufficient scope for collecting data that is more comprehensive, so that users can identify the stage of their mental health.

The aim of the present research [41] is to predict depression risk through the context-DNN model and multiple regression. As the article states, depression is a mental illness that is brought on for several reasons. For this reason, research is conducted on mental disorders and therapy to understand a patient's state. However, according to the author, in the case of predicting depression, there is hardly any research. Moreover, there is a high chance of depression recurring once cured. That is why, the author proposed the idea of implementing context-DNN and multiple-regression to prevent depression. This context-DNN model collects data from the environment around people and other context information and identifies the factors that can lead to depression. The research faced the most difficulty at the time of the conducting the first performance of the proposed context-DNN. The evaluation result was unfit and inaccurate. Nevertheless, as the test continued, the performance kept on improving. Eventually, the performance accuracy and recall were much better than general DNN. In the future, the author would like to adopt a model that allows for individualized health management by categorizing contexts into internal and external contexts and identifying the impact of external and internal variables that affect each.

In this research [42], the authors introduce a cognitive behavioral therapy system, often known as a therapy Chatbot that can respond to a user's health and informational demands, with a special emphasis on the treatment element that detects a person's state of depression. Firstly, the authors list the drawbacks of conventional psychic treatment and discusses how a therapy Chatbot can address them. Secondly, the authors highlight characteristics that encourage the use of online therapy, such as the prevention of excessive social isolation, the facilitation of communication, online peer support, and the enhancement of participation in activities. Moreover, the authors suggest an approach that comprises developing a Chatbot utilizing machine learning (ML) and natural language processing (NLP). According to the authors, some features of the therapy bot (T-bot) should include serving as a personal assistant, gaining hybrid attention, fighting depression, having a machine that converses like a human, providing the best solution and feedback for every query, a simplified menu or a search bar, direct menu links, and displaying depression and therapy level. Furthermore, the researchers provide a logical technique for calculating the severity of depression. To conclude, the authors address certain research-related issues with therapeutic Chatbots and offer some recommendations, such as surveying other research disciplines and learning from them, performing more complete experiments, modernizing publication standards, and establishing best practices guidelines for therapy Chatbot research.

In this paper [43], the authors focus on using data analytic techniques to protect the privacy of personal health records to overcome the shortcomings of previous methodologies. First, the authors highlight the significance of safeguarding personal health data privacy. Moreover, the authors demonstrate how two traditional privacy-preserving approaches, such as De-Identification, Notice, and Consent, work and then analyzes their drawbacks. Furthermore, the authors provide a privacy protected data analysis approach to minimize unauthorized access, use, or disclosure of private information. The proposed solution involves using an encryption mechanism to protect electronic medical records maintained on a unified cloud server. The encoding technique converts ASCII binary data to RADIX-64 notations. In addition, the authors use a neural network algorithm to implement the data association approach. Finally, the authors underline the main disadvantages of discovering the association mining design and promoting research without jeopardizing patients' privacy.

In this paper [44], the authors stress the need for establishing an artificial intelligence-based medical Chatbot that can detect an illness and offer basic information about it before contacting a physician. The authors state that their suggested system employs an intelligent system to respond to queries if the solution present in the database and data is stored in the form of a pattern template, with SQL being used to manage the database. The proposed system architecture includes several processes like UI(User Interface), tokenization, stop word removal, feature extraction(N-gram, TF-IDF), sentence similarity, retrieving the matched sentence, result, and analysis. In the UI, the client types the query. The UI sends user queries to the Chatbot app. The literary experience preprocessing stages include tokenization, stop word removal, n-gram, TF-IDF, and cosine likeness of feature extraction. The knowledge database stores questions and answers and can be retrieved. In conclusion, the authors emphasize the significance of this secure, effective healthcare Chatbot system.

In this paper [45], the authors introduced a two-staged rank regression method for detecting clinical depression. This model intends to work around any inconsistencies in the relationship between changes in a person's speech characteristics and fluctuations in their levels of depressive symptoms. The two-stage approach derives a series of scores from speech features to predict depression. Ranking values are derived from predetermined non-discrete partitions of the feature space that correlate depression score clusters and indicate views about how strongly they are connected to different stages of depression scores. Three key phases comprise the two-stage rank regression approach. In the first phase, the score axis is partitioned into appropriate sections. The second phase is to develop a collection of functions that model the link across processing layers and partitions. Finally, the last stage is to use the magnitude with which these models reflect the input data. The two-stage structure proved to be extremely adaptable when used with various feature sets and machine learning approaches. Consistent performance in each execution was attained while predicted under AVEC-2013 testing conditions. This test demonstrated the viability of employing the framework while predicting the level of depression. Another important finding in this paper is that combining two-stage systems continuously raises system efficiency; this is a new finding in the field of speech-based depression forecasting.

The authors of this work [46] suggest an edge computing-enabled federated-learning-based prototype system for participatory model training across many distributed users in the creation of healthcare-related systems. Several researchers have suggested the edge computing structure to simplify the processing of data at the network's edge to eliminate the requirement for data transfer to the cloud. As the personal data can be maintained on local IoT devices during model training, the edge-computing model enhances privacy protection. The authors created a dynamic two-period arrangement with correlated user types to encourage users' long-term participation. The distinction between a traditional contract and a dynamic contract is that the first-period contract must account for the second-period asymmetric information, wherein the user types are unknown.

Chapter 3

Methodology

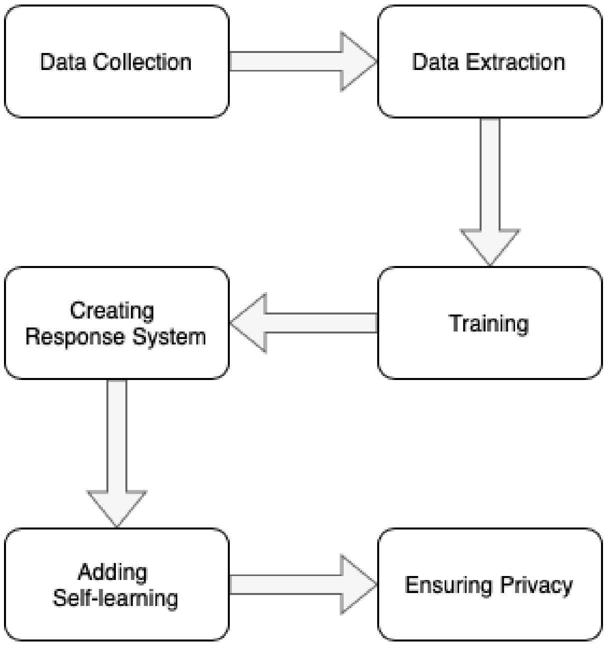

Figure 3.1: Steps For Making the chatbot

We are conducting this research to devise a Chatbot that can provide suggestions for any psychological problem by having text conversations with users. Along with its efficiency, it will maintain the privacy of users' conversations so that people can share their sensitive data without hesitance. However, to fulfill the purpose of developing this kind of Chatbot, it is imperative to collect a huge amount of data. Conversely, even without having a large amount of data, we can create this Chatbot by including a self-learning feature. Fig 3.1 shows our work plan, following which we were able complete our research effectively.

3.1 Dataset Collection and Extraction

We chose a dataset that had counseling conversations from an online source named Kaggle [47]. There are a total 2130 questions and its corresponding answers available in this dataset. Sometimes, one question comes up multiple times, as there can be more than one response for a particular question. There are eight columns available in the dataset of which we select three columns to make our proposed Chatbot, namely "questions", "index numbers of the questions" and "the answers of the questions".

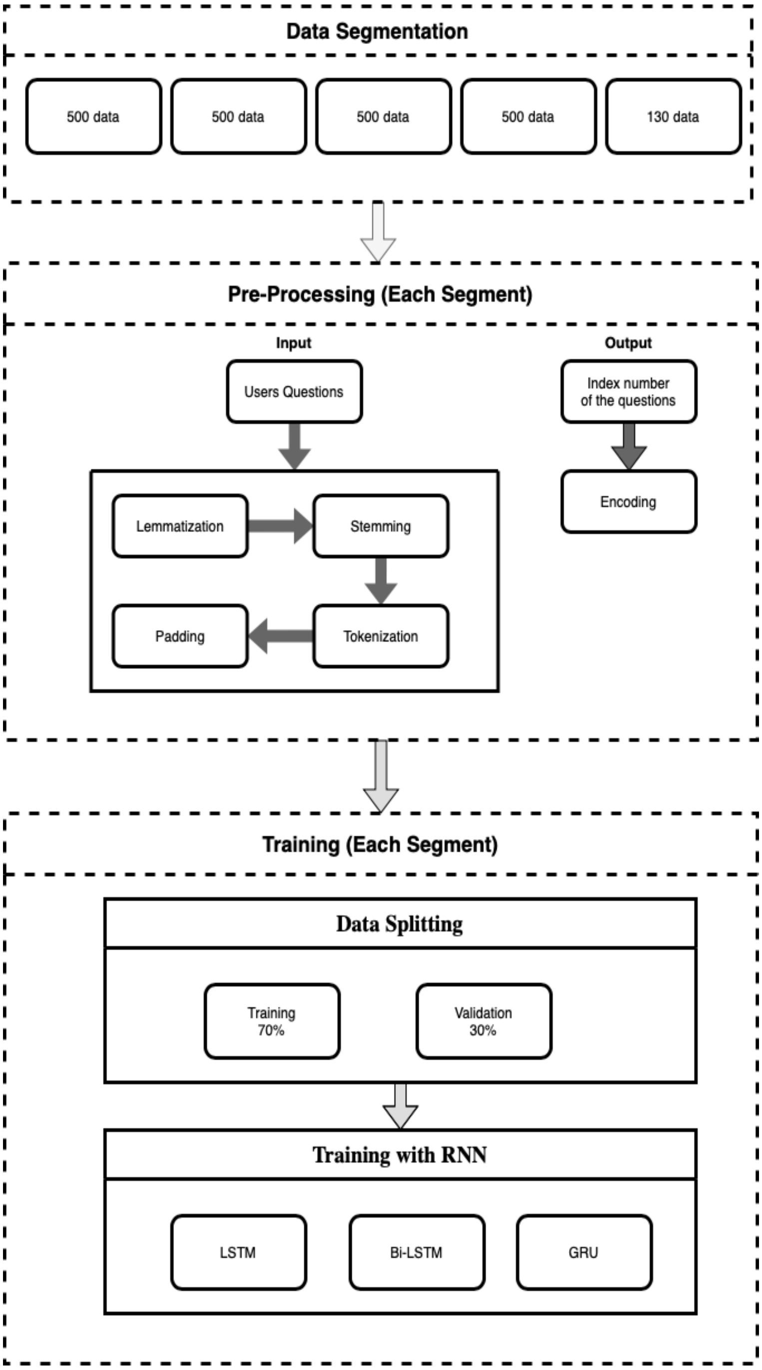

Figure 3.2: Steps for training the chatbot with extracted data

3.2 Data Segmentation

One of the major motives of our proposed chatbot is to ensure the accessibility of lots of users with a comparatively less powerful machine. In order to accomplish this, we decided not to train all the data altogether. Instead, we divided the data into few segments and trained each segments separately. This way, we can train all the data in a less powerful GPU. Here, we divide the data into 5 segments.
Training Data: We use the trainng data to train the model. The model will be able to learn from the training data. Here we have provided 70% data for training in each segment.
Validation Data: We use the validation data to know performance of model with unknown new data. Here we have provided 30% data for validation in each segment.

Segment number	data amount	Data Splitting	
		Amount of training data	Amount of validation data
1	500	70%	30%
2	500	70%	30%
3	500	70%	30%
4	500	70%	30%
5	130	70%	30%

Table 3.1: Summary of Segments

3.3 Data Pre-Processing

Prior to starting the task of training the model, we focused on the pre-processing of the data. As in the data set, we may not have found the data in an accurate format for training purpose. Also, computers can not understand the human level language. To make all the data perfect for training, we had to focus on pre-processing. We completed the task of input data pre-processing in four steps. These are lemmatization, stemming, tokenization and padding. We have just encoded the value of the outputs in the pre-processing part.

3.3.1 Input Pre-Processing

Lemmatization

After extracting all the inputs from the dataset, we initially lemmatized every input to identify the lemma of a word based on intended meaning [47]. We have utilised a python library named 'WordNetLemmatizer' to complete the task of lemmatization [48].

Stemming

Next we have focused on stemming the lemmatised inputs [49]. This stemming algorithm is helpful to convert a word to a root word. In this reasearch, we have used "PorterStemmer" for Stemming [50].

Tokeniztion

Tokenization is one of the most important part of data Pre-Processing [51]. As computers cannot understand the human language, we have to convert all input questions into numerical format. After tokenizing, we obtain the input as numerical matrices. For this research, input is the user's questions and output is their corresponding index number. Therefore, we tokenized the value of the inputs by "tokenizer" function from the Tensorflow library [52].

Padding

After tokenization has converted every string to matrix format, the dimensions of all matrices may not be equal. We apply padding to bring all the matrices into one specific dimension. We used "pad_sequences" function from the Tensorflow library to complete this task [53].

3.3.2 Output Pre-Processing

Encoding

As computers do not recognize the human level language, we have to convert all the outputs so that the computer can understand the output. This is known as encoding. For our research, we have encoded the output using a built-in python library named LabelEncoder [54]. In this case, all the corresponding index numbers of the questions are set as the outputs.

3.4 Data Training

For training the model, we decided to use the RNN algorithm. To find the best RNN algorithm among LSTM, Bi-LSTM and GRU for our chatbot, we created the three models using these algorithms. Then we compile these three models with the Adam optimizer, sparse categorical cross-entropy loss, and accuracy metrics. Next, we trained the models with the three algorithms [55][56][57]. Then we selected the best one by comparing the performance of each model. After selecting our model, we created our chatbot using that RNN algorithm.

Layer (type)	**Output Shape**	**Param #**
input_1 (InputLayer)	[(None, 552)]	0
embedding (Embedding)	(None, 552, 10)	37580
lstm (LSTM)	(None, 552, 10)	840
flatten (Flatten)	(None, 5520)	0
dense (Dense)	(None, 816)	4211376
Total params: 4,249,796 Trainable params: 4,249,796 Non-trainable params: 0		

Table 3.2: Model Overview of LSTM

Layer (type)	Output Shape	Param #
input 1 (InputLayer)	[(None, 552)]	0
embedding (Embedding)	(None, 552, 128)	481024
bidirectional (Bidirectio nal)	(None, 552, 128)	98816
bidirectional_1 (Bidirect ional)	(None, 128)	98816
dense (Dense)	(None, 816)	105264
Total params: 783,920 Trainable params: 783,920 Non-trainable params: 0		

Table 3.3: Model Overview of Bi-LSTM

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 552)]	0
embedding (Embedding)	(None, 552, 10)	37580
gru (GRU)	(None, 552, 10)	660
flatten (Flatten)	(None, 5520)	0
dense (Dense)	(None, 816)	4211376
Total params: 4,249,616 Trainable params: 4,249,616 Non-trainable params: 0		

Table 3.4: Model Overview of GRU

3.5 Create Response System

3.5.1 Give input

First, the user gives input. After that, the user gets a response from each model. Since we have divided the data into five segments and created each model with the data of each segment, five output responses are predicted from the five models.

3.5.2 Predict output

From each model, one output will be predicted. The prediction process is similar for every model. After giving input, the input is lemmatized and then this lemmatized value is stemmed. After that, we tokenized the stemmed value. Next, we apply padding to the tokenized value according to the highest dimension of each model. After that, the output is predicted. The predicted output is the encoded value of the index number. To decode this value, we use LabelEncoder python library. The same process is followed to predict the output from each model.

3.5.3 Find Similarity

After predicting the output from each model, we find the corresponding question that is available in this model for the predicted index number. After finding all questions from each model using the index number, we measure the cosine similarity between the padding value of the user input and the padding value of every question [58].

3.5.4 Getting Answer

After measuring the cosine similarity from each model, we select the model that provides the highest cosine similarity among all the models. Next, we select the predicted output from this model as the final output. Here, the output is the index number of the answer. Then the corresponding answer to this index number will be extracted from the dataset, and the user will see that answer as the response to their query. Sometimes, there may be multiple answers available for a question. In that case, the person randomly gets one answer. When a person does not satisfy, the user can see rest of the answers. Additionally, if none of these responses pleases the user, the feature named "self learning" can assist the users in knowing the accurate solution.

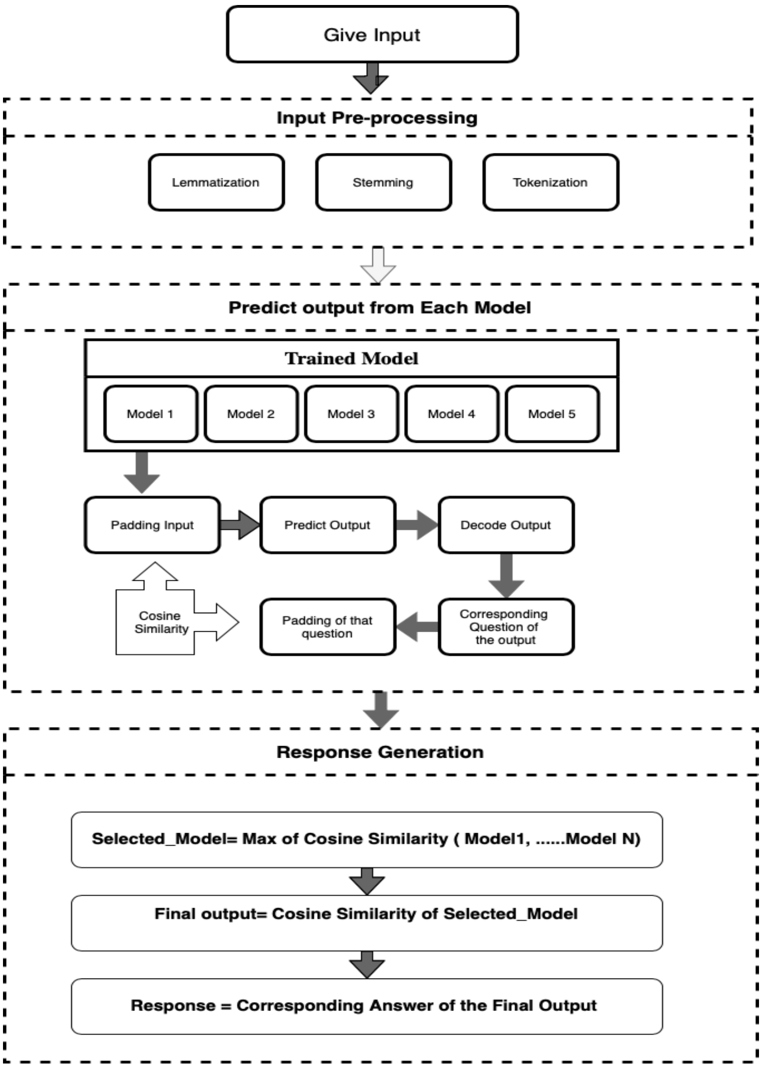

Figure 3.3: Steps For Creating Response System

3.6 Providing Privacy

Due to a feature named "Self-Learning," the chatbot will be able to learn from the users' conversations. However, as one of our motive is to ensure the privacy of the users' conversations, we only save the tokenized value of the user input. Therefore, only the numerical format of user inputs will be saved in the database. While the Chatbot will able to predict the output based on the tokenized value better, by just seeing these numerical values, no one can comprehend the actual conversations of the users. Hence, user's privacy concern is successfully handled in this way.

3.7 Self-Learning

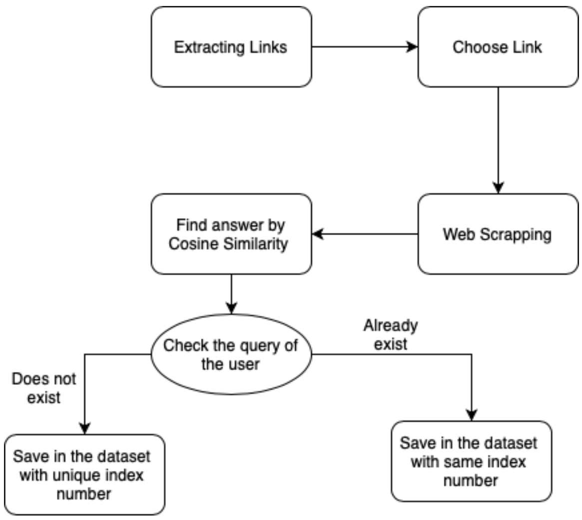

Figure 3.4: Workflow of Self-learning

One of the best features for this Chatbot is having the self-learning ability. As it is virtually impossible to manage a dataset where every question of every mental healthcare problem and its corresponding answers are available, users may sometimes receive inaccurate answers. Whenever a user might think an answer is incorrect, they can use this amazing feature of our Chatbot.

3.7.1 Extracting Links

Firstly, the user has to choose a hyperlink where solutions of his/her mental health problem could be found. So, some hyperlinks will be extracted using the google search library [59]. From all the extracted hyperlinks, the user can select any particular link.

3.7.2 Web scrapping

We have to extract all the information of the web article from the preferred link of the user. There is a Python library named "newspaper" that has been used to extract the whole article from the link [60].

3.7.3 Finding answer from the article

After the task of extracting the article is completed, we have to find out the exact answer from the article. The cosine similarity algorithm has been used to accomplish this goal [61].

3.8 Sample Response getting from the user input

Sample Input:I'm facing severe depression and anxiety and I just feel like I'm going through a lot. This really distracts me and I cant get my mind off the things that are bothering me. How do I overcome this anxierty and depression?

predicted output (index number)				
model 1	model 2	model 3	model 4	model 5
3	215	405	812	19
Cosine similarity score between user input and predicted output				
model 1	model 2	model 3	model 4	model 5
0.99998	0.29985	0.39849	0.21685	0.628555

From the above table, model 1 has provided most similar score. Hence, we have chosen the answer from model 1. So the user will get corresponding answer of index number 3.

Output: Have you used meditation or hypnosis? Relaxing the mind and connecting with your true self is a great way to calm your thoughts and get to peace and calm. Hypnosis and meditation have helped a lot of people with anxiety and depression. Google hypnotherapists near me or write for a while about what is going on.

Chapter 4

Implementation & Results

4.1 Comparing RNN Models

To make the chatbot, we have decided to use the best RNN algorithm among LSTM, Bi-LSTM and GRU. To find the best algorithm, we have chosen 2130 questions and their corresponding index numbers. After that, we have trained the chatbot using these three algorithms, these 2130 questions and their corresponding index numbers. After training, we evaluate the three RNN models based on training accuracy, training loss, validation accuracy and validation loss. The below table summarises the performance of each RNN algorithm.

Algorithm	**Parameter**	**Training**	**Validation**	**Epoch**
LSTM	Accuracy	0.9484	0.6917	30
	Loss	0.1054	5.1919	
Bi-LSTM	Accuracy	0.9148	0.6745	40
	Loss	0.4785	3.4855	
GRU	Accuracy	0.9497	0.6901	30
	Loss	0.0972	3.4262	

Table 4.1: Performance of RNN Models

From the table and below graphs, it can say that GRU is providing best performance among these three algortihms.

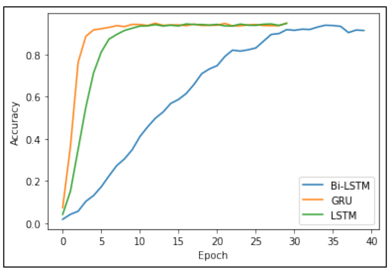

Figure 4.1: Training Accuracy

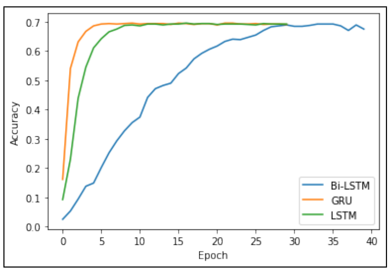

Figure 4.2: Validation Accuracy

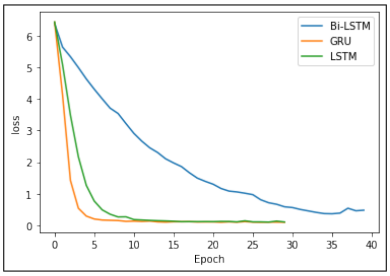

Figure 4.3: Training Loss

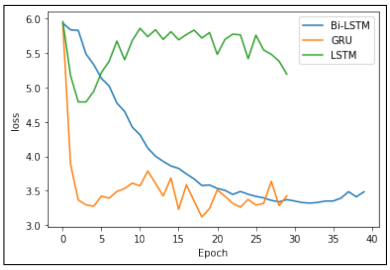

Figure 4.4: Validation Loss

4.2 Final Results Analysis

To evaluate the exactness of the final predicted outputs, we chose all the questions from the dataset and predicted the outputs of these questions through our proposed training method and our proposed response system. Then we train a model using these questions and outputs. After that, we also chose these same questions and their corresponding index numbers from the dataset and trained another model using these data. After training these two models, we compared their performances to discern the difference between the final predicted output and the actual output of the dataset.

Model	Epoch	Accuracy	Loss
Predicted output	27	0.9457	0.1066
Dataset output	27	0.9423	0.1028

From the above table, it can be seen that the two models provide almost similar accuracy and loss after running 30 epochs. In the below two graphs, we can also see that two lines are overlapping with each other. Moreover, the increasing rate of accuracy and the decreasing rate of loss in both models are very similar. So it can be said that the two models are providing almost similar performance in every sector. Consequently, our proposed chatbot will be able to provide almost the same response as a traditionally RNN trained chatbot. Here, the traditionally trained RNN model is providing outstanding accuracy. Hence, it can be said that the proposed chatbot will also perform exceptionally well in the sector of providing responses. Therefore, we can state that our proposed algorithm is good at providing excellent performance while ensuring the data privacy in a comparatively less powerful machine.

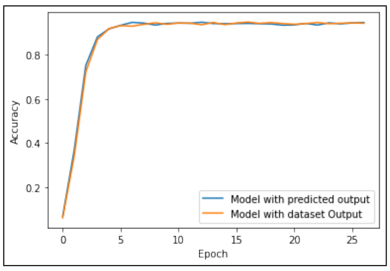

Figure 4.5: Training Accuracy

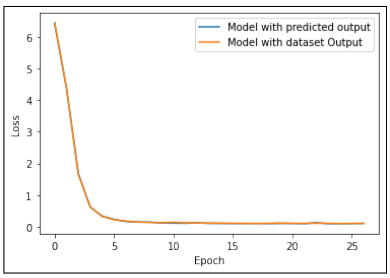

Figure 4.6: Training loss

4.3 Sample test conversion

The below table 4.1, shows the sample conversation between Chatbot and the users. Here, the Chatbot did not give the same reply for the same question every time as every problem can have multiple solutions. For this reason, this Chatbot provides different responses for same questions. Moreover, it is not necessary to ask the exact same question like in the database in order to receive an accurate response because this Chatbot can understand the intention of users. Even if the user's query is only remotely similar to a particular question of the database, this Chatbot can still deliver the correct reply.

User Input	**Output**
I have bipolar II disorder, I'm addicted to alcohol and weed, and I'm hopeless. I keep drinking even though it's harming myself and others.	You are not hopeless, as you can see there are many people who care about your well being and believe you can overcome this. I would suggest that you first get evaluated for your alcohol consumption. Alcohol is one of the addictions that you may need to seek inpatient treatment for. If not inpatient then be monitored by a doctor. Once you are evaluated and or complete inpatient treatment I would suggest you participate in a form of outpatient therapy on a consistent basis.
I have bipolar II disorder, I'm addicted to alcohol and weed, and I'm hopeless. I keep drinking even though it's harming myself and others.	You may feel hopeless but YOU are not hopeless. Addictions of any sort are difficult to overcome, especially when they serve to bury pain and suffering that one is experiencing. It is not impossible to overcome alcohol or drug use/abuse/dependence on your own, but you will likely find much greater success with the help of a therapist or other support system such as rehabilitation or Alcoholics Anonymous. I suggest doing a bit of research to see what type of help is available and feasible for you in your area and go from there. Know that recovery takes time, willingness, and effort. Don't give up and remember that you are not hopeless. You can make the choice to change your habits and learn new ways of healthy coping. Best of luck to you!

User Input	Output
I have a long history of depression and I'm beginning to have anxiety. I have low self esteem .	Anxieties are an adrenal problem; Clean them out with a proper detox, using the food built for mankind, and a herbal protocol;Maybe throw in some fasting here and there to kick the kidneys into high gear and get the adrenals pumping... Every loss is a gain, so losing a car means you no longer hold responsibility to keep and maintain it...If you\'re really up for it, some contemplation (that is keep one thought *lightly* on your mind allllllll day; that is just focus upon it from time to time, "Man, I notice that the sky is really blue today... and the air is really crisp today..."); after 3-5 days of contemplation, see what you notice...
For the last, few days I have been going through so many nightmares.	Being able to know you feel anxiety and write about it, is the first step to addressing and handling it!Generally, anxiety is deep fear of not being able to handle what comes up in life. \xa0\xa0Somehow the person was insufficiently nurtured and so felt \xa0insecure when very young.Usually the person had to fend on at least a psychological and emotional level for themselves before reaching an age when doing so would have been reasonable.Their inner feeling of overwhelmed from when very young, hasn't faced the reality that the grown person is now capable, even if this takes some practice. \xa0Try asking yourself what you are afraid of and theorize how you would handle these situations as a grown person.Also, sometimes anxiety comes from feeling lonely. \xa0This loneliness is reminiscent of the loneliness that the grown person now, felt when being left to take care of situations as a child which were too difficult and complex for any child to address.

Table 4.2: Sample Conversations

Chapter 5

Future Works

We have made an outstanding psychological counselling Chatbot using the RNN algorithm that has the ability to ensure the privacy of user conversations and train this model in comparatively less powerful computers too. In future, we plan to add a video conferencing feature so that the Chatbot can provide a more comprehensive psychological counselling service. As it is easier to detect emotion from facial expressions than text messages. Additionally, we will look into adding multiple language support since people find it easier to communicate in their native language. Finally, we will work towards decreasing the amount of time complexity in response system. This will be beneficial for the users to get faster responses.

Conclusion

Today, the world is making progress towards accepting and acknowledging the importance of mental health. Yet, there are still breakthroughs left to be made in facilitating the provision of easily accessible mental health care to the general populace. In this research, we have developed a Chatbot that has the ability to provide mental healthcare through text conversations. This pioneering Chatbot can protect the privacy of the users so that they can candidly share their sensitive problems without hesitation. Due to the self-learning function, we did not need to collect a lot of data. This ability of our conversational agent helps to improve its ability to provide constant mental health care.

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