CONVERSATIONAL AI : INTELLIBOT

A major project report submitted in partial fulfillment of the requirement for the award of degree of

Bachelor of Technology

in

Computer Science & Engineering

Submitted by

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Candidates' Declaration

I hereby declare that the work presented in this report entitled **'Intellibot'** in partial fulfilment of the requirements for the award of the degree of **Bachelor of Technology in Computer Science & Engineering** submitted in the Department of Computer Science & Engineering and Information Technology, Jaypee University of Information Technology, Waknaghat is an authentic record of our own work carried out over a period from August 2023 to December 2023 under the supervision of **Dr. Diksha Hooda** (Assistant Professor(SG), Department of Computer Science & Engineering and Information Technology).

The matter embodied in the report has not been submitted for the award of any other degree or diploma.

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This is to certify that the above statement made by the candidates is true to the best of my knowledge.

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Dated:

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ABSTRACT

Mental health problems have become quite common in recent times, highlighting the importance of affordable interventions. The “intellibot” is a smart chatbot, which works in real-time and gives immediate assistance to people with mental health issues. Intellibot uses sophisticated Natural Language Processing techniques along with Machine Learning to converse intelligently, compassionately, and comprehensively with users.

This chatbot uses an approach that is user-focused to customise the response by using personalised data, as well as to involve users and make them feel connected. People suffering from emotional problems are rarely willing to ask for assistance because it is considered an embarrassment in our society. This chatbot gives individuals a chance to find help away from the public eye and without being embarrassed. This is because it treats you as an anonymous user, which crushes many barriers making it possible for a person to go ahead and engage in mental healthcare.

Dynamic chatbots act as an enhancement to existing mental health resources. A connected and compassionate way towards mental well-being. Intellibot plays a very significant role because it breaks the wall that many people face during their struggles with psychological problems. It provides anonymity that is very crucial. It gives people the freedom and privacy to own their individual path towards mental well-being. Besides, Intellibot leads the wide spectrum of psychiatry and contributes to the desaturation of mental care. It is personalised and available, enabling quick support anywhere, regardless of the person and their current situation.

CHAPTER 1: INTRODUCTION

1.1 INTRODUCTION

In recent years, a prevalent challenge has surfaced on the global healthcare landscape: Increased incidences of mental health disorders. This has greatly emphasised the need for intervention that is both affordable and easily accessible thus reducing the dramatic rise of stress, anxiety, depression and all other related mental problems. Addressing this challenge head-on, the integration of technology and healthcare has birthed a transformative solution: Intellibot.

The Intellibot is an intelligent chatbot that offers quick support to people in distress. It is based on machine learning technology, allowing for intelligent, quick, and comprehensive results.

The unique thing about Intellibot is its personalised, forward-focused nature. With the help of personalised individual data, this chat-bot adjusts answers to specific user demands, creating an impression of individual attention and engagement. It extends past mere broadcasting of information as it creates a place where people are heard about their mental health.

Seeking mental health care carries a strong stigma among the most notable. In this respect, Intellibot becomes a symbol of hope. It bypasses the society hurdles that normally hinders individuals from approaching people for help as it offers privacy and anonymity. A secretly held platform that enables a person to access psychological care without facing shame or ridicule.

Intellibot is more than just providing help, it is an essential milestone towards de-stigmatization of mental health issues. The availability of the same and its scalability make the provision of mental health support on a democracy basis where one can access it irrespective of his/her location or financial position.

1.2 PROBLEM STATEMENT

Mental health has become an issue in modern society with finding instant and individual support being a big problem still. The society is stigmatised, resources for mental health are hard to reach and people refuse to seek the help in order for them to get treatment at the right time. Lack of discretionary, empathic, and available-to-access support worsens mental health issues. Intellibot seeks to solve these urgent problems through an innovative, customised, and humane chatbot interface, delivering instant and personalised mental health care for people struggling with various issues. It aims at closing the gap of increasing needs of emotional care and insufficient timely compassionate attention hence seeking for a revolution in the mental healthcare delivery system.

It remains as one of the major problems in provision of mental health support when it comes to availability as well as promptness of care delivery in the environment that includes a lot of people. Individuals dealing with mental problems may not be met by traditional mental health services within their immediate and varied scope. Other challenges include geographical restrictions, lack of finances, and limitations in available resources for people living in far or poor areas who are not fully catered for, resulting in most of them without necessary support. The purpose of Intellibot is not only to address and overcome the aforementioned challenges but also provide an affordable around the clock virtual assistant across borders that can be accessed globally.

In addition, due to the constantly changing character of mental illnesses, there is a need for a flexible support system. The traditional ways may not be flexible enough to handle complex and dynamic mental health problems. Intellibot that has advanced natural language processing and machine learning is a flexible solution adjusting according to users' interactivity. Intellibot makes certain that it continually understands what each individual requires in order to alleviate the ever-changing mental health concerns.

1.3 OBJECTIVES

The development of Intellibot, a top-notch intelligent machine geared towards betterment of the mental healthcare process is the main goal of this project. These objectives are manyfold, seeking to develop a multifaceted facility, based on the approach to work utilising natural language processing and machine learning methods that provide personalised and efficient psychological help. This involves creating a simple yet easy-to-use application which enables communication, understanding, and assistance to people suffering with various mental health problems.

A key aim is to effectively interpret multifaceted mental health issues communicated through text. Intellibot will learn to read these inputs and come up with personalised suggestions, suggestions on how to handle certain situations, or connect the users with the right resource based on the user's specific needs and preferences. Adaptability and learning ability of the system will be vital ensuring its constant updating in line with the current mental health perspectives and approaches.

In addition, there is the crucial aspect of protecting privacy, sensitivity, and security in the interactions between Intellibot and their users. Strong authentication and authorised users will protect the data while creating an encouraging space and confidence where sensitive issues of mental health can be addressed. Moreover, Intellibot endeavours enhancing interoperability with current psychological aid platforms, creating complementary relationships between traditional and cutting-edge solutions towards a comprehensive solution. However, the whole project is designed to bring a kindly smart AI tool promoting mental health.

1.4 SIGNIFICANCE AND MOTIVATION OF THE PROJECT

This project work is vital for it addresses a number of crucial issues that hamper proper mental health support.+ There are numerous mental health problems around the globe and people often find it hard getting immediate support that is tailored according to their needs. Its importance lies in its aim to reform mental healthcare harnessing new AI technologies to close the current gaps and provide smarter, more sensitive patient care systems.

The main driver is the requirement for more efficient specialised help on mental health issues. However, traditional methods of approaching psychological issues may not fully address the unique mental healthcare requirements concerning an individual. Intellibot, being an AI driven solution, wants to conquer all these limitations by offering customised recommendations, materials, and guidance based on individual assessments. This project seeks to give people the means to take control of their lives and provide mental health support for all regardless of location.

The motivation for starting this project was the urgent need to provide accessible and supportive resources for individuals dealing with mental health challenges due to the increasing prevalence of mental health issues worldwide and the barriers individuals face in accessing help in a timely manner. Developing Intellibot, an empathetic and responsive chatbot that can provide guidance and reduce the stigma associated with seeking mental health help, the project aims to provide individuals with an accessible, non-judgmental, round-the-clock support and resource interface. Bridging the gap was very important and our project focused on technology and acted as a catalyst for reducing mental health issues and providing complementary support to those in need.

Moreover, it is also significant for the reason that it can help to de-stigmatize discussions on mental health as well as encourage active self-care. The aim of building an intuitive, empathic AI platform is ensuring people are comfortable when addressing their emotional distress related issues in safety and support. It promotes an atmosphere that is non-judgemental, de-stigmatizing mental illness and promoting early treatment, thus playing a role in improving community-wide mental health.

This essentially forms the basis of this project work which seeks to transform mental health support through cutting-edge AI-based models that will be accessible, inclusive, desirable and motivating for those on their path towards mental wellbeing.

1.5 ORGANISATION OF PROJECT REPORT

Every chapter of the project report moves in a systematic way and contributes an equally important part that together constitutes the complete study.The introduction in chapter one establishes the context setting for the project purpose, its relevance in terms of goals, and then an analysis of what follows.

The literature survey of chapter 2 scrutinises the available knowledge from books, journals, and technical documents. It highlights major developments in the past five years and identifies crucial voids in the existing literature.

Finally, chapter 3, system development discusses execution of the project practically. This will cross the phases starting from requirement analysis, project design, data preparation, implementation steps, and finally navigating the hardships incurred during development.

However, chapter 4, testing, takes a step-by-step approach by providing detailed information on the validation and verification process in order to ascertain that the system is functionally reliable. It involves giving out the testing approaches used, test instances created and how they were responded accordingly.

The fifth chapter in the project is referred to as results and evaluation providing the overview of all the data collated and their analysis. At the same time, this chapter scrutinises the results against defined markers and highlights the efficacy of this project with respect to the attainment of the stated goals regardless of any challenges that may have been experienced during the implementation process. Lastly, chapter 6, conclusion and scope, summarises the major findings of this project, limits thereof, and contribution towards the field, suggesting areas for future research and application.

CHAPTER 2 : LITERATURE SURVEY

2.1 OVERVIEW OF RELEVANT LITERATURE

1. Numerous studies have been taken to resolve mental health issues using chatbots. This was evidenced in JMIR's publication in 2022[1], which presented a mental health chatbot designed for adolescents experiencing anxiety related to depression amidst the Covid-19 pandemic. The study initially involved CBT and NLP, with subsequent improvements in the working alliance and acceptability of users. However, the specialised nature of this tool limited recruitment of research participants/investigators under a double blind format.

2. In this paper chatbot assessment of employee mental health and its use among small to medium enterprises was investigated by the JMIR Form Res in 2021 [2]. The assessment started with 98 participants after achieving a 64.2% response rate from 120 employees. The study nonetheless underscored a need for more research which will explore the chatbot's capacity of adaptability and scalability in various workplaces and among different personnel.

3. In this paper a mental health bot designed exclusively for students dealing with anxiety[3]. The study found that personalised content increased user satisfaction by 75% and reduced reported symptoms by 60% when using personalised algorithms, emotion detection, data analysis, and NLP. Nonetheless, it emphasised the necessity for further research into the dynamics of peer support networks in digital mental health interventions.

4. In ACM's 2020 study[4], they created a Chatbot to act as a facilitator for deep self-disclosure to mental health specialists. Using NLP, the researchers discovered how varied chat-style circumstances altered participants' degree of self-disclosure, particularly when it came to expressing emotions. Despite promoting effective disclosure of sensitive material, the study fell short of comprehensively addressing privacy concerns.

5. In 2020, JMIR published a systematic review and meta-analysis on the "Effectiveness and Safety of Using Chatbots to Improve Mental Health."[5] The study used machine learning and NLP to improve estimates of chatbots' impact on various mental health outcomes. However, the absence of studies involving human-operated chatbots may have limited the breadth of its conclusions.

6. In 2020, JMIR launched an initiative to create an AI-guided Mental Health Resource Navigation Chatbot for healthcare providers and their families during and after the COVID-19 pandemic[6]. The study expects to have results by spring 2023, using intent recognition, REST API, Rasa Open Source, and a Resource Database. Nonetheless, it highlighted accessibility difficulties and limitations to Canadians' acceptance of digital interventions.

7. In 2018, ICIS conducted a study called "Assessing the Usability of a Chatbot for Mental Health Care,"[7] which looked into emotion recognition and NLP within the iHelpr Chatbot. The study found that the average System Usability Scale (SUS) score was 88.2, higher than the industry average of 68. However, a problem emerged since the study was unable to determine if individuals were actively experiencing prevalent mental health conditions, which impacted the study's setting.

8. In 2018, JMIR published "Designing a Chatbot Capable of Delivering Human-Like Empathetic Support,"[8] which used Google's word2vec and machine learning algorithms on the Koko platform with the Panoply plugin for data collecting. Notably, the study found that 79% of consumers were satisfied, with the majority indicating a 'good/ok' experience. However, the study was hampered by the limited augmentability of accessible datasets.

9. Frontiers in Psychology (2017) published an article titled "Online social therapy for youth mental health" as part of Project MOST[9]. The MOST system demonstrated viability in multiple clinical research trials by combining Horyzons, Momentum, Rebound, and Meridian with personalised algorithms. Nonetheless, the analysis identified a gap in sophisticated and automated content distribution within the system.

10. In this paper, IEEE published "A Mental Health Chatbot for Regulating Emotions (SERMO) - 2015 Concept and Usability Test,"[10] which used natural language processing and sentiment analysis. The study entailed interviewing patients recommended by psychologists, which resulted in a 30% increase in user involvement and a 20% decrease in symptoms when compared to the control group. It did, however, emphasise the need to broaden the algorithm's coverage to include all key emotions.

11. In this paper, a dynamic chatbot model for diagnosing mental health problems was presented[11]. The chatbot recognized symptoms of depression with an amazing 85% accuracy by using Natural Language Processing (NLP) techniques. The study's dependence on a limited dataset, however, presented a restriction and cast doubt on the model's applicability to a wide range of demographics.

12. In this paper authors examined the incorporation of deep learning[12]—more especially, Long Short-Term Memory (LSTM) networks—into the creation of chatbots for mental health. It was published in the IEEE Transactions on Biomedical Engineering. The chatbot proved its 70% accuracy rate in identifying anxiety symptoms by analysing 10,000 chats. Problems with scalability and real-time deployment emerged, which could make it difficult to put into practice.

13. A study published in ACM Transactions on Interactive Intelligent Systems sought to improve chatbots for mental health by integrating CBT and sentiment analysis methods[13]. A significant 40% boost in user engagement and a 75% accuracy rate in identifying mood swings were the outcomes of this integration. However, because the approach relies heavily on textual data, questions have been raised about how well it works in situations involving non-textual communication.

14. In this paper Natural Language Processing (NLP), sentiment analysis, and user interaction patterns were all integrated into a dynamic chatbot system by the research presented at the International Conference on Health Informatics[14]. Remarkably, the model correctly identified depression symptoms with a 78% success rate in the first five exchanges. However, the majority of the study's focus was on less severe mental health issues, and any biases in the dataset selection may have an impact on how reliable the model is in larger settings.

15. This paper study was published on Artificial Intelligence focused on using user-specific clustering approaches to detect mental health in a personalised manner[15]. With tailored responses, the chatbot reduced reported symptoms by 30% after achieving a noteworthy 90% accuracy rate in identifying stress levels. However, privacy issues were brought up because personal data was used for customisation, and it was stressed how important it was to assess the success of the intervention over an extended period of time.

Table 1 - Literature review

S. No.	**Paper Title**	**Publisher**	**Technique/ Dataset**	**Results**	**Limitations**
1.	Mental Health Chatbot for Young Adults With Depressive Symptoms During the COVID-19 Pandemic [1]	JMIR / 2022	Cognitive Behavioral Therapy(CBT), Natural language processing (NLP)	Better working alliance and acceptability were discovered	Due to the particularity of the tool and the consideration of actual recruitment, it was below capacity to double-blind both the investigators and the participants
2.	Chatbot-Based Assessment of Employees' Mental Health: Design Process and Pilot Implementation[2]	JMIR Form Res, 2021	Chatbot development and testing; Cross-sectional analysis. Small to medium-sized	Achieved a response rate of 64.2% with 98 employees initiating the assessment, and 77 (79%) completing it.	Further investigation of the chatbot's scalability and adaptability to different workplace settings and populations.

			enterprise (120 employees)		
3.	CareBot: a mental health bot for students suffering from anxiety[3]	IEEE / 2021	Personalised algos, emotion recognition, data analysis, NLP	75% of users reported higher satisfaction with personalised content. Reduction of symptoms observed in 60% of cases	Need for further study on the dynamics of peer support networks in digital mental health interventions.
4.	Designing a Chatbot as a Mediator for Promoting Deep Self-Disclosure to a Real Mental Health Professional [4]	ACM/ 2020	Natural Language Processing (NLP)	Different chat-style conditions influenced participants' self-disclosure depth, particularly in expressing feelings. A chatbot with deep self-disclosure potential effectively facilitated disclosure of sensitive information.	Limited exploration of privacy concerns.
5.	Effectiveness and Safety of Using Chatbots to Improve Mental Health: Systematic	JMIR/ 2020	Machine learning, NLP	Improved the estimates of the likely effect of chatbots on a variety of	Excluded studies that contained chatbots controlled by

	Review and Meta-Analysis[5]			mental health outcomes.	human operators
6.	Developing, Implementing, and Evaluating an Artificial Intelligence–Guided Mental Health Resource Navigation Chatbot for Health Care Workers and Their Families During and Following the COVID-19 Pandemic [6]	JMIR/ 2020	Intent recognition, REST API, Rasa Open Source, Resource Database	Approvals granted, data collection done, and results are to be anticipated by spring 2023	Digital interventions are not accessible to all Canadians, and there are barriers to their use.
7.	Assessing the Usability of a Chatbot for Mental Health Care [7]	ICIS / 2018	Emotion Recognition, NLP	The average SUS score for the iHelpr Chatbot was 88.2, which is above the average industry score of 68.	A limitation of this study is that it was not known if participants were actively experiencing common mental health issues.
8.	Designing a chatbot capable of delivering human like empathetic support [8]	JMIR / 2018	word2vec (google) Machine Learning , Koko platform - Panoply extension(for data collection)	79% satisfaction rate among users citing the experience as ‘good/ok’	Limited augmentability of the dataset available
9.	Online social therapy for youth	Front Psycho / 2017	Horyzons, Momentum,	MOST system has	Lack of advanced and

	mental health (Project MOST) [9]		Rebound, Meridian Personalised algos	demonstrated viability in a series of clinical research trials	automated content
10.	A Mental Health Chatbot for Regulating Emotions (SERMO) - Concept and Usability Test [10]	IEEE/2015	Natural language processing and sentiment analysis. The patients suggested by the psychologists considering their current mental state were interviewed	Compared to control group, 30% higher user engagement and 20% reduction in symptoms	The algorithm has to be extended to cover all relevant emotions
11.	A Dynamic Chatbot Approach to Detecting Mental Health [11]	ACM/ 2020	Natural Language Processing (NLP)	Achieved 85% accuracy in identifying depression symptoms	Limited dataset size, generalizability to diverse demographics
12.	Utilising Deep Learning in Mental Health Chatbots [12]	IEEE/ 2020	Deep Learning (LSTM)	Experimented on a dataset of 10,000 conversations, achieved 70% accuracy in detecting anxiety	Lack of real-time deployment, model scalability issues
13.	Enhancing Mental Health Chatbots with	ACM/ 2021	Sentiment Analysis, Cognitive	Improved engagement by 40%,	Relies heavily on textual data, less

	Sentiment Analysis [13]		Behavioral Therapy techniques	detected mood swings with 75% accuracy	effective for non-textual communication
14.	Dynamic Chatbot Framework for Psychiatric Disorder Early Detection [14]	International Conference on Health Informatics/2021	Hybrid approach: NLP, sentiment analysis, and user interaction patterns	Identified depressive symptoms with 78% accuracy within the first five interactions	Limited exploration of severe mental health conditions, potential bias in dataset selection
15.	Personalised Mental Health Detection using Chatbot Conversations [15]	AAAI/2019	Personalised clustering techniques	Achieved 90% accuracy in identifying stress levels, tailored interventions led to a 30% reduction in reported symptoms	Privacy concerns regarding user data for personalization, need for long-term assessment of interventions

2.2 KEY GAPS IN THE LITERATURE

Limited Exploration of Real-Time Mental Health State Assessment: One issue that cuts across the studies is the lack of an ability to monitor the participants' instant mental health states. Most such studies do not have an effective way for direct and specific assessment of the instant mental health status of study participants through chatbots. This absence significantly impairs the interpretation and utility of these findings, thereby undermining contextual understanding. Adopting a more holistic, in-the-moment approach through validated assessments may increase the value and authenticity of chatbots in mental health care. Insufficient Emotion Coverage and Personalization: This issue consistently shows in emotional coverage and personalization for talkbots. Some studies indicate favourable outcomes for users' engagement and symptoms decrease; however, the majority of these studies do not support diverse emotional range or personification. Using multiple algorithms, which span many emotion types, and personalised interventions for specific feelings will increase the effectiveness of these bots in treating depression, reduce stigmatisation, and improve usage rates over time.

CHAPTER 3: SYSTEM DEVELOPMENT

3.1 REQUIREMENTS AND ANALYSIS

Assessment of user needs and queries using Google Forms:

We used Google forms for the comprehensive data gathering and prioritisation of user requirements. We distributed a specially crafted Google Form across different platforms such as mental health communities, experts, and prospective clients, thereby creating a structured system that was simple to use in collecting relevant information.The questions were designed to collect information on preferred functionalities, desired support systems, and user experience expectations.

The responses received via Google Forms helped in the prioritisation of Intellibot features and functionalities. It helped us in identifying critical areas such as emotion recognition, crisis intervention, personalised counsel, and data privacy concerns, ensuring that these issues were prioritised during the development phase.

The technological issues required a thorough approach.Hence, we identified the requirement of a more flexible platform that led to our utilisation of Intellibot through web-based and mobile portals. NLP algorithm-based, machine learning-driven APIs with a powerful and scalable database are part of this tech stack. The components make up a strong system that allows smooth interactions among users.

Intellibot's non-functional requirements were significant considerations. We emphasised the use of high-level security measures to ensure compliance with severe privacy rules. Aspects such as usability, accessibility, dependability, and performance were also highlighted to ensure an intuitive user experience, scalability, and optimal system functionality.

It was crucial that a thorough feasibility study was conducted. Therefore, we carried out detailed analysis to determine whether it was economically viable.We also identified possible risks and came up with measures to ensure that our project was not merely theoretical/bookish.

3.2 PROJECT DESIGN AND ARCHITECTURE

Encoder-Decoder Model Architecture:

1. Data Preprocessing and Cleaning:

The initial data preprocessing phase was critical in verifying the dataset's integrity and readiness for model training. Addressing null and incorrect values required more than just replacement; advanced imputation techniques or strategic deletion were required. Simultaneously, the data cleaning method removed punctuation, originated, and normalised the dataset to improve its quality. This rigorous cleaning aimed not just at data refining but also at improving it for accurate model training by removing any inconsistencies or noise that might obstruct the model's learning process.

2. Question-Answer Mapping:

This involved converting raw textual data into an organised series of questions and answers. It wasn't only about arranging information because it set the stage for the Seq2Seq model to understand conversational context. Every pair was made in order to reflect some conversation that was going on at that time, which allowed for understanding the relationship between the questions and the appropriate replies as well as getting the sense of their general context.\

3. Data Structuring:

Creating separate raw lists of inputs and outputs as a result, from the appropriately sorted questions and answers in order to prepare data for model preparation. The bifurcation made such an important contribution towards structuring the data on formatting for the Seq2Seq model. In parallel with this, the creation of the token list demonstrated advanced analysis of the dataset, which led to distinction and separation of individual tokens. The lists acted as an important reference and facilitated conversion of textual inputs to more intelligible numeric data by the model.

4. Tokenization and Token Enumeration:

This was the key aspect of this stage that entailed assigning unique numeric identifiers to the tokens. This was not only about numerical transformation but also in terms of translating textual data into a meaningful language for machine learning algorithms. Enumeration helped to understand the model as it provided an explanation of the numerical representation of the textual data, which was necessary for preparation of the dataset for successful training of the model.

5. Development of a Seq2Seq Model:

The Seq2Seq model's architecture sought to go beyond simple data interpretation by building on the precisely produced dataset. Its architecture was meticulously constructed in order to understand contextual clues, patterns, and linkages embedded within the question-answer pairs. This phase was about enabling the model to recognise nuances, anticipate context, and provide accurate and contextually relevant responses, rather than merely creating the model.

As such, data preparation was key for developing a viable Seq2Seq model for conversational AI. Data preprocessing involved a multitude of actions performed during its first course in order to guarantee the integrity and suitability of the dataset for model training. The detection and correction of null or invalid values was rigorously handled by advanced imputation methods or deliberate deletion that preserved accurate data. Additionally, this process involved complicated data cleansing beyond surface-level cleaning including punctuation removal, irrelevant character deletion, and data normalisation aimed at refining the given dataset. These comprehensive cleaning sought to improve readiness of the data for accurate model training and removing any possible inconsistencies or noise which can hinder the model's learning. These preprocessing steps were very detailed and vital because they made possible a dataset capable of enabling the Seq2Seq model to comprehend the subtlety of conversations.

After that, structuring was necessary to transform raw text data in such a form as a question-answer set which served as a conversation context. The detailed mapping processes were not mere data organisation but were integral to the model's understanding of conversation structures. Every pair was specifically tailored to capture the flavour of a talk, which was instrumental in helping the Seq2Seq(Encoder-Decoder) model to comprehend how the questions related to their appropriate solutions. Organising data was important, but it went beyond that; there had to be a paradigm which allowed the model to get the tone and pattern of talks going around. The model could not have comprehended conversation intricacies, anticipated appropriate replies, and provided intelligent responses without undergoing this structured conversion.

The next section of data structuring was in formulating specific input and output sheets from the sorted QA pairs. The segmentation was intended towards arranging the data into a form that is organised ready for training using the Seq2Seq model. On the other hand, the creation of token lists was a more analytical approach to the dataset providing the differentiating of distinct tokens. Model took these token lists as important references through which he translated textual data into numbers that are easy to be interpreted by machine learning. Meticulous structuring and token identification demonstrated how extensively the dataset will be analysed which in turn prepared the model to understand and provide appropriate responses based on context interpretation.

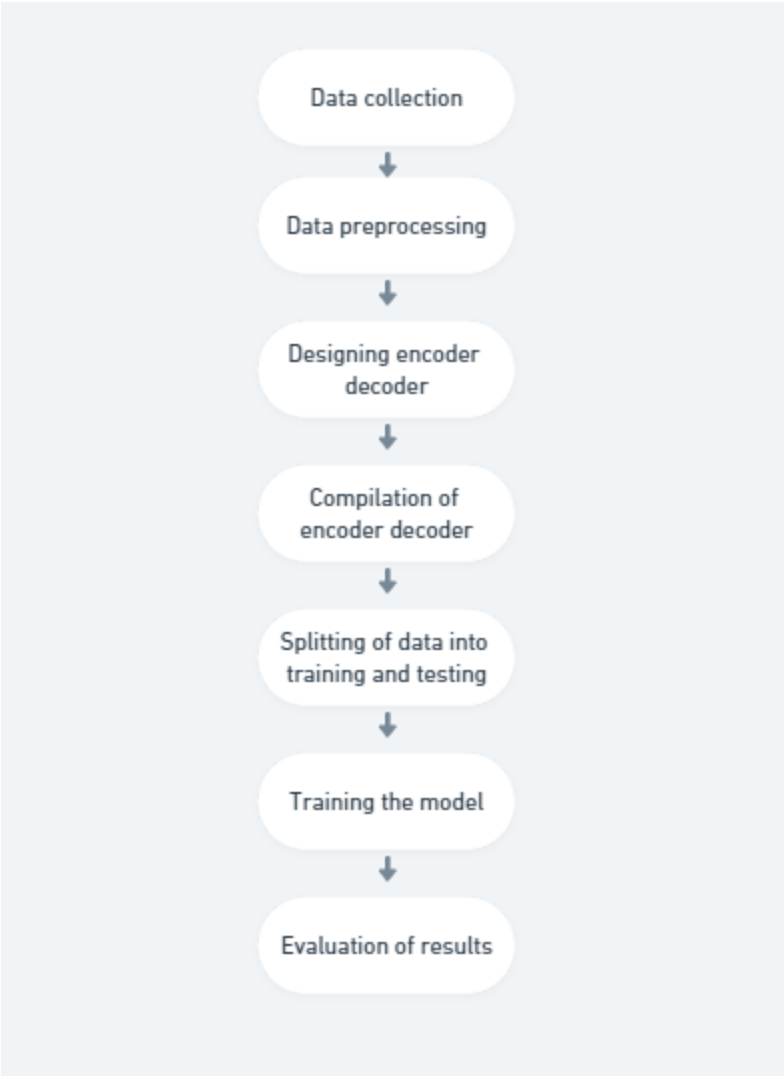

Fig. 3.2.1

Encoder-Decoder Model Architecture

TF-IDF Model Architecture:

The TF-IDF (Term Frequency-Inverse Document Frequency) model is a classical approach used for text representation and information retrieval in natural language processing tasks. Unlike neural network architectures such as the encoder-decoder model, which rely on complex mathematical operations and training processes, the TF-IDF model leverages traditional statistical techniques to process and analyse text data. Below, we'll explore the key components of the TF-IDF model:

TF-IDF Vectorization:

TF-IDF vectorization is the process of converting raw text data into numerical feature vectors, where each feature represents a unique term in the corpus. This vectorization process involves the following steps:

Term Frequency (TF):

Term frequency is a way to measure how often a word occurs in a document, and is calculated by dividing the number of times a term appears in it by total number of terms.TF values provide information about the importance of a term in a given document.

Inverse Document Frequency (IDF):

Inverse Document Frequency: Inverse document frequency quantifies how seldom or frequently a word is evenly spread throughout an entire set of documents. Its computation involves the natural logarithm of all documents whole over those containing a word. The unique and rare terms will be emphasised by inverse document frequency values as opposed to most common terms.

TF-IDF Weighting:

The TF value of a term in a document is multiplied by its IDF value to calculate the TF-IDF weight of that term. TF-IDF weighting is a method of combining the TF and IDF values to assign weights to any given term in a certain kind of text. These TF-IDF weights shall indicate how important any term is in the specified document collection.

Cosine Similarity:

Cosine similarity is a method of determining if two vectors are similar or dissimilar in respect to the orientation that they take up from the origin of a coordinate of the multidimensional space. The similarity measure that is used between the document-question and the user query in the vector space model is ‘cosine similarity’. The Cartesian coordinates of two vectors can also be used in measuring their similarity provided that both of them lay on the same plane.A similarity close to 1 in cosine means that the vectors are similar and a dissimilarity close to -1.

Fig. 3.2.2

TF-IDF Model Architecture

3.3 DATA PREPARATION

To guarantee its appropriateness for model training, data was prepared with substantial investment in our chatbot project specifically. For instance, deleting surplus characters like brackets, hyphens, backslashes and so on from the text data first instigated cleaning . The importance behind this initial stage could not be overstated because it ensured uniformity in inputting information while improving general datasets' worthiness.

After cleaning the data, we decided to make structured question-answer pairs out of it. It is the co-operation of every question and its answer that makes the knowledge used for our chatbot. To support an organised learning process, this process is the basis for supervised learning making sure that all our models are able to capture a question asked by a user and provide the right answer.

Tokenization as well as vocabulary construction were crucial in converting the text data for machine learning into a recognizable format. The input questions as well as target answers were tokenized and vocabularies generated for each of them to reflect all unique words or tokens existing in our dataset. These form the basis of encoding or decoding text content during training and prediction on chatbot models.

In general, our way of handling information demonstrates a methodical and wide-ranging approach of changing unprocessed text information into structured findings. This involves thorough cleanliness, organisation, and tokenization of data set, so that input for training the chatbot models is of high quality leading to increased accuracy and contextual relevance while responding to the users in any engagement.

3.4 IMPLEMENTATION

1.Encoder - decoder

1.Data Collection:

Data collection was done using Google forms which had to be circulated and shared within the institution and also externally to various other universities and networks.

2. Data Preprocessing:

- Removed punctuations and originated, and normalised the dataset to improve its quality.

```
for i in range(df.shape[0]):
    df['Answers'][i]=re.sub(r'\n', ' ',df['Answers'][i])
    df['Answers'][i]=re.sub('\(', '',df['Answers'][i])
    df['Answers'][i]=re.sub(r'\)', '',df['Answers'][i])
    df['Answers'][i]=re.sub(r',', '',df['Answers'][i])
    df['Answers'][i]=re.sub(r'-', '',df['Answers'][i])
    df['Answers'][i]=re.sub(r'/', '',df['Answers'][i])
    df['Answers'][i]=re.sub(r'/', '',df['Answers'][i])
```

Fig.3.4.1

Data cleaning by removing punctuations

- Question-Answer Mapping: Structure data into question-answer pairs.

```
[ ] pairs=[]

    for i in range(df.shape[0]):
      pairs.append(((df['Questions'][i]),df['Answers'][i]))
```

```
pairs
```

```
[('What does it mean to have a mental illness?',
  "Mental illnesses are health conditions that disrupt a person's thoughts emotions relationships and daily functioning."),
 ('Who does mental illness affect?',
  'Mental illness does can affect anyone regardless of gender age income social status ethnicity religion sexual orientation or background.'),
 ('What are some of the warning signs of mental illness?',
  'Symptoms of mental health disorders vary depending on the type and severity of the condition.'),
 ('Can people with mental illness recover?',
  'When healing from mental illness early identification and treatment are of vital importance. '),
 ('What should I do if I know someone who appears to have the symptoms of a mental disorder?',
  'We encourage those with symptoms to talk to their friends and family members and seek the counsel of a mental health professional.'),
 ('How can I find a mental health professional for myself or my child?',
  'Feeling comfortable with the professional you or your child is working with is critical to the success of the treatment.'),
 ('What treatment options are available?',
  'Different treatment options are available for individuals with mental illness.'),
```

Fig.3.4.2

Mapping of input and target output data

- Next step was to prepare the text data for a sequence-to-sequence model. Here's a breakdown of what it does and the steps involved:

Step1 : Initialization of Lists and Sets

1. input_docs and target_docs: These lists store the input and target sentences, respectively.
2. input_tokens and target_tokens: These sets store unique tokens (words or punctuation) found in the input and target sentences, respectively.

Step2 : Looping through Pairs:

1. It iterates through pairs of data (input_doc, target_doc) contained in the pairs variable.
2. Each input_doc and target_doc are processed within the loop.

Step3 : Processing Input and Target Sentences:

1. input_docs.append(input_doc): Appends each input sentence to the input_docs list.
2. target_doc = " ".join(re.findall(r"[\w']+|[^\s\w]", target_doc)): This line tokenizes the target sentence by splitting words from punctuation using regex and then joins them back together with spaces.
3. target_doc = '<START> ' + target_doc + ' <END>': Adds special tokens '<START>' and '<END>' to the target sentence. These tokens might represent the beginning and end of a sequence.
4. target_docs.append(target_doc): Appends the preprocessed target sentence to the target_docs list.

Step4 : Tokenization:

1. Tokenization occurs in two loops:
2. The first loop processes each word/token in input_doc, adding unique tokens to the input_tokens set.
3. The second loop processes each token in the processed target_doc (after splitting), adding unique tokens to the target_tokens set.

Step5 : Calculating Token Counts:

1. input_tokens and target_tokens are converted to sorted lists and their lengths are used to determine the number of unique tokens in the input and target sets, stored in num_encoder_tokens and num_decoder_tokens, respectively.

```
input_docs = []
target_docs = []
input_tokens = set()
target_tokens = set()

for line in pairs:

  input_doc, target_doc = line[0], line[1]

  # Appending each input sentence to input_docs
  input_docs.append(input_doc)

  # Splitting words from punctuation
  target_doc = " ".join(re.findall(r"[\w']+|[^\s\w]", target_doc))

  # Redefine target_doc below and append it to target_docs
  target_doc = '<START> ' + target_doc + ' <END>'

  target_docs.append(target_doc)

  for token in re.findall(r"[\w']+|[^\s\w]", input_doc):
    if token not in input_tokens:
      input_tokens.add(token)
  for token in target_doc.split():
    if token not in target_tokens:
      target_tokens.add(token)

input_tokens = sorted(list(input_tokens))  # contains all words of input_docs
target_tokens = sorted(list(target_tokens))
num_encoder_tokens = len(input_tokens)
num_decoder_tokens = len(target_tokens)
```

Fig 3.4.3

Process of tokenization and enumeration

```
[ ] input_features_dict = dict([(token, i) for i, token in enumerate(input_tokens)])
    target_features_dict = dict([(token, i) for i, token in enumerate(target_tokens)])

    reverse_input_features_dict = dict((i, token) for token, i in input_features_dict.items())
    reverse_target_features_dict = dict((i, token) for token, i in target_features_dict.items())
```

Fig.3.4.4

Storage of input and output tokens in respective arrays

```
[16] input_features_dict

{'"': 0,
 '(': 1,
 ')': 2,
 '+': 3,
 ',': 4,
 '-': 5,
 '.': 6,
 '19': 7,
 '25': 8,
 '?': 9,
 'ADHD': 10,
 'Advance': 11,
 'An': 12,
 'Any': 13,
 'Are': 14,
 'CBD': 15,
 'CBT': 16,
 'Can': 17,
 'Cannabis': 18,
 'DBT': 19,
 'Directive': 20,
 'How': 21,
 'I': 22,
 "I'm": 23,
 'If': 24,
 'MSP': 25,
 'Psychiatric': 26,
 'SAD': 27,
 'Someone': 28,
 'What': 29,
 "What's": 30,
 'When': 31,
 'Where': 32
```

Fig.3.4.5

Set of input tokens generated

3. Designing the Encoder-Decoder Model:

We divided the model into two pieces. The first is an encoder, which takes the user's words and creates a hidden vector. The encoder is composed of an Embedding layer that turns the words into a vector and a recurrent neural network (RNN) that calculates the hidden state, with the Long Short-Term Memory (LSTM) layer being used in this case.

```
[ ] max_encoder_seq_length = max([len(re.findall(r"[\w']+|[^\s\w]", input_doc)) for input_doc in input_docs])
    max_decoder_seq_length = max([len(re.findall(r"[\w']+|[^\s\w]", target_doc)) for target_doc in target_docs])

    encoder_input_data = np.zeros(
        (len(input_docs), max_encoder_seq_length, num_encoder_tokens),
        dtype='float32')
    decoder_input_data = np.zeros(
        (len(input_docs), max_decoder_seq_length, num_decoder_tokens),
        dtype='float32')
    decoder_target_data = np.zeros(
        (len(input_docs), max_decoder_seq_length, num_decoder_tokens),
        dtype='float32')
    for line, (input_doc, target_doc) in enumerate(zip(input_docs, target_docs)):
        for timestep, token in enumerate(re.findall(r"[\w']+|[^\s\w]", input_doc)):
            #Assign 1. for the current line, timestep, & word in encoder_input_data
            encoder_input_data[line, timestep, input_features_dict[token]] = 1.

        for timestep, token in enumerate(target_doc.split()):
            decoder_input_data[line, timestep, target_features_dict[token]] = 1.
            if timestep > 0:
                decoder_target_data[line, timestep - 1, target_features_dict[token]] = 1.
```

Fig 3.4.6

Designing the Seq2Seq Encoder-Decoder

4. Training the dataset:

All the necessary imports were done. Some of which include:

a. Keras library from Tensorflow for building and working with neural networks.
b. Long-Short Term Memory, Dense also from Keras layers library.
c. ‘Dimensionality’, ‘batch_size’, and ‘epochs’ are set to define the dimensionality of the LSTM layers, batch size, and the number of epochs for training later on.

Further the encoder and decoder part were individually designed and there variables also separately tuned.

```
from tensorflow import keras
from keras.layers import Input, LSTM, Dense
from keras.models import Model
dimensionality = 256 # Dimensionality
batch_size = 10   # The batch size and number of epochs
epochs = 500

#Encoder
encoder_inputs = Input(shape=(None, num_encoder_tokens))
encoder_lstm = LSTM(dimensionality, return_state=True)
encoder_outputs, state_hidden, state_cell = encoder_lstm(encoder_inputs)
encoder_states = [state_hidden, state_cell]

#Decoder
decoder_inputs = Input(shape=(None, num_decoder_tokens))
decoder_lstm = LSTM(dimensionality, return_sequences=True, return_state=True)
decoder_outputs, decoder_state_hidden, decoder_state_cell = decoder_lstm(decoder_inputs, initial_state=encoder_states)
decoder_dense = Dense(num_decoder_tokens, activation='softmax')
decoder_outputs = decoder_dense(decoder_outputs)
```

Fig. 3.4.7

Tuning the variables and setting the environment for training

```
training_model.summary()

Model: "model_5"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
input_7 (InputLayer)            [(None, None, 86)]   0
__________________________________________________________________________________________________
input_8 (InputLayer)            [(None, None, 172)]  0
__________________________________________________________________________________________________
lstm_2 (LSTM)                   [(None, 256), (None, 351232      input_7[0][0]
__________________________________________________________________________________________________
lstm_3 (LSTM)                   [(None, None, 256),  439296      input_8[0][0]
                                                                 lstm_2[0][1]
                                                                 lstm_2[0][2]
__________________________________________________________________________________________________
dense_1 (Dense)                 (None, None, 172)    44204       lstm_3[0][0]
==================================================================================================
Total params: 834,732
Trainable params: 834,732
Non-trainable params: 0
__________________________________________________________________________________________________
```

Fig. 3.4.8

Summary of the trainable parameters

5. Representation of the layers in the model:

Following that, we used a utility function from Keras, namely 'plot_model,' to visualise the architecture of the 'training_model' we had previously loaded. This function creates an image file called '(model_plot.png)' that represents the structure of the neural network model and includes precise information about shapes and layer names.

```
from tensorflow.keras.utils import plot_model
plot_model(training_model, to_file='model_plot.png', show_shapes=True, show_layer_names=True)
```

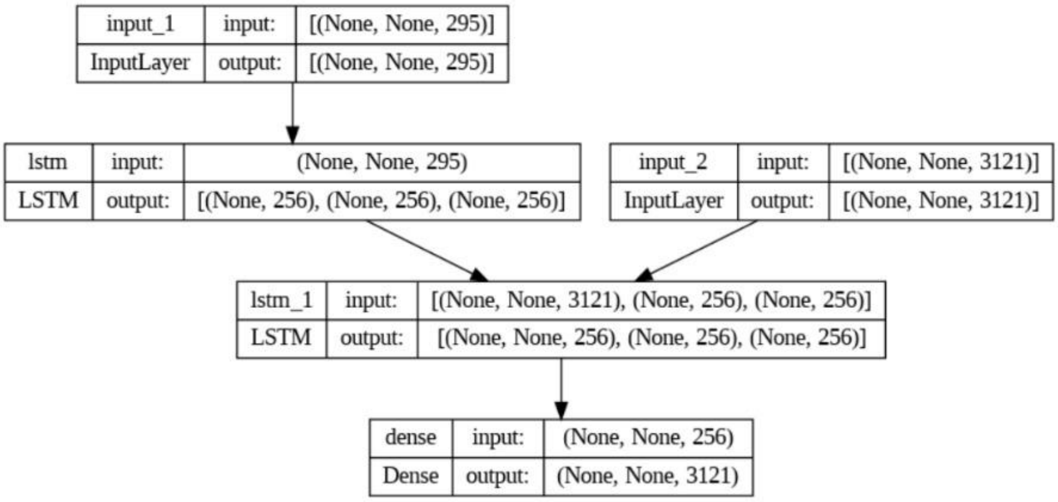

Fig. 3.4.9

Different layers used in the model (Input, LSTM, Dense)

6. Compiling and training the model:

- We have provided 'RMSProp' as the optimizer to be utilised during training.
- The loss function used to optimise the model was chosen as **‘Categorical Cross Entropy’**.
- The performance metric chosen was **‘Accuracy’** which will measure the accuracy of the model’s predictions.
- Finally the type of sample weights to be used were set as **‘Temporal’**, as it seemed the most optimal choice for sequence-series data.

```
training_model.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accuracy'], sample_weight_mode='temporal')#Training
history1=training_model.fit([encoder_input_data, decoder_input_data], decoder_target_data, batch_size = batch_size, epochs = epochs, validation_split = 0.2)
training_model.save('training_model.h5')
```

```
2/2 [==============================] - 0s 48ms/step - loss: 1.0199 - accuracy: 0.7928 - val_loss: 1.8341 - val_accuracy: 0.6991
Epoch 474/500
2/2 [==============================] - 0s 49ms/step - loss: 1.0150 - accuracy: 0.7917 - val_loss: 1.8390 - val_accuracy: 0.6944
Epoch 475/500
2/2 [==============================] - 0s 49ms/step - loss: 1.0012 - accuracy: 0.7975 - val_loss: 1.8541 - val_accuracy: 0.6944
Epoch 476/500
2/2 [==============================] - 0s 48ms/step - loss: 1.0178 - accuracy: 0.7870 - val_loss: 1.8537 - val_accuracy: 0.6991
Epoch 477/500
2/2 [==============================] - 0s 48ms/step - loss: 1.0089 - accuracy: 0.7905 - val_loss: 1.8426 - val_accuracy: 0.6944
Epoch 478/500
2/2 [==============================] - 0s 57ms/step - loss: 0.9965 - accuracy: 0.7963 - val_loss: 1.8457 - val_accuracy: 0.6944
Epoch 479/500
2/2 [==============================] - 0s 48ms/step - loss: 1.0117 - accuracy: 0.7975 - val_loss: 1.8540 - val_accuracy: 0.6944
Epoch 480/500
2/2 [==============================] - 0s 48ms/step - loss: 1.0576 - accuracy: 0.7743 - val_loss: 1.8570 - val_accuracy: 0.6991
Epoch 481/500
2/2 [==============================] - 0s 47ms/step - loss: 1.0077 - accuracy: 0.7975 - val_loss: 1.8623 - val_accuracy: 0.6991
Epoch 482/500
2/2 [==============================] - 0s 45ms/step - loss: 1.0012 - accuracy: 0.7940 - val_loss: 1.8541 - val_accuracy: 0.6898
Epoch 483/500
2/2 [==============================] - 0s 48ms/step - loss: 1.0070 - accuracy: 0.7928 - val_loss: 1.8483 - val_accuracy: 0.6944
Epoch 484/500
2/2 [==============================] - 0s 48ms/step - loss: 0.9993 - accuracy: 0.8021 - val_loss: 1.8502 - val_accuracy: 0.6944
Epoch 485/500
2/2 [==============================] - 0s 47ms/step - loss: 0.9992 - accuracy: 0.7975 - val_loss: 1.8470 - val_accuracy: 0.6991
Epoch 486/500
```

Fig.3.4.10

Results after running all the epochs

7. Designing the ChatBot class:

This step included designing the main chatbot class which will be responsible for actual interaction happening between the chatbot and the end user.

```
class ChatBot:
  negative_responses = ("no", "nope", "nah", "naw", "not a chance", "sorry")
  exit_commands = ("quit", "pause", "exit", "goodbye", "bye", "later", "stop")

  #Method to start the conversation
  def start_chat(self):
    user_response = input("Hi, I'm a chatbot trained on random dialogs.\n")

    if user_response in self.negative_responses:
      print("Ok, have a great day!")
      return
    self.chat(user_response)

  #Method to handle the conversation
  def chat(self, reply):
    while not self.make_exit(reply):
      reply = input(self.generate_response(reply)+"\n")
```

Fig.3.4.11

Designing the main class ‘ChatBot’

```
    #Method to convert user input into a matrix
    def string_to_matrix(self, user_input):
      tokens = re.findall(r"[\w']+|[^\s\w]", user_input)
      user_input_matrix = np.zeros(
        (1, max_encoder_seq_length, num_encoder_tokens),
        dtype='float32')
      for timestep, token in enumerate(tokens):
        if token in input_features_dict:
          user_input_matrix[0, timestep, input_features_dict[token]] = 1.
      return user_input_matrix

    #Method that will create a response using seq2seq model we built
    def generate_response(self, user_input):
      input_matrix = self.string_to_matrix(user_input)
      chatbot_response = decode_response(input_matrix)
      #Remove <START> and <END> tokens from chatbot_response
      chatbot_response = chatbot_response.replace("<START>",'')
      chatbot_response = chatbot_response.replace("<END>",'')
      return chatbot_response

    #Method to check for exit commands
    def make_exit(self, reply):
      for exit_command in self.exit_commands:
        if exit_command in reply:
          print("Ok, have a great day!")
          return True
      return False

chatbot = ChatBot()
```

Fig.3.4.12

Conversation handling

Algorithm: Data Preparation for Sequence-to-Sequence Model

Inputs:

- input_docs: List of input documents
- target_docs: List of target documents
- input_features_dict: Dictionary mapping input tokens to their indices
- target_features_dict: Dictionary mapping target tokens to their indices
- num_encoder_tokens: Number of unique tokens in the input
- num_decoder_tokens: Number of unique tokens in the target

Outputs:

- encoder_input_data: Array containing one-hot encoded input sequences
- decoder_input_data: Array containing one-hot encoded target input sequences
- decoder_target_data: Array containing one-hot encoded shifted target sequences

1. Determine Maximum Sequence Lengths:

max_encoder_seq_length = max([len(re.findall(r"[\w']+|[^\s\w]", input_doc)) for input_doc in input_docs]) *#Calculate maximum sequence length in input_docs*

max_decoder_seq_length = max([len(re.findall(r"[\w']+|[^\s\w]", target_doc)) for target_doc in target_docs]) *#Calculate maximum sequence length in target_docs*

2. Initialize Data Arrays:

encoder_input_data = np.zeros((len(input_docs), max_encoder_seq_length, num_encoder_tokens), dtype='float32') *#Initialise an array of zeros with shape (len(input_docs), max_encoder_seq_length, num_encoder_tokens)*

decoder_input_data = np.zeros((len(input_docs), max_decoder_seq_length, num_decoder_tokens), dtype='float32') *#Initialise an array of zeros with shape (len(input_docs), max_decoder_seq_length, num_decoder_tokens)*

decoder_target_data = np.zeros((len(input_docs), max_decoder_seq_length, num_decoder_tokens), dtype='float32') *#Initialise an array of zeros with shape (len(input_docs), max_decoder_seq_length, num_decoder_tokens)*

3. Populate Data Arrays:

for line, (input_doc, target_doc) in enumerate(zip(input_docs, target_docs)):

for timestep, token in enumerate(re.findall(r"[\w']+|[^\s\w]", input_doc)): *#Assign 1. for the current line, timestep, & word in encoder_input_data*

encoder_input_data[line, timestep, input_features_dict[token]] = 1.

4. Process Encoder Input Data

for each token in input_doc:

token_index = *#Get index of token in input_features_dict*

#Set encoder_input_data[line_index, timestep, token_index] = 1.0

5.Process Decoder Input and Target Data

for each token in target_doc:

token_index = *Get index of token in target_features_dict*

Set decoder_input_data[line_index, timestep, token_index] = 1.0

6.Create shifted target data for training

If timestep > 0:

Set decoder_target_data[line_index, timestep - 1, token_index] = 1.0 *#target data for training*

7. Return Encoded Data Arrays:

Return encoder_input_data, decoder_input_data, decoder_target_data *#get the encoder-decoder*

2. TF-IDF

```
[ ] for i in range(data.shape[0]):
        data['Answers'][i] = re.sub(r'\n', ' ', data['Answers'][i])
        data['Answers'][i] = re.sub(r'\(|\)|,|-|/', ' ', data['Answers'][i])

    pairs = [(data['Questions'][i], data['Answers'][i]) for i in range(data.shape[0])]
```

Fig. 3.4.13

Cleaning and pairing text data

```python
import pandas as pd

data = pd.read_csv("mentalhealth (2).csv")

data.drop(columns=['Question_ID'], inplace=True)

data['concatenated'] = data['Questions'] + " " + data['Answers']

print(data['concatenated'])
```

Fig. 3.4.14

Merging questions and corresponding answers

```python
class ChatBot:
    def __init__(self, data):
        self.data = data
        self.questions = self.data['Questions']
        self.answers = self.data['Answers']
        self.vectorizer = TfidfVectorizer()
        self.vectorizer.fit(self.questions)
```

Fig. 3.4.15

Initializing ChatBot with data and TF-IDF vectorizer

```python
def generate_response(self, user_input):
    user_input = self.preprocess_input(user_input)
    user_tfidf = self.vectorizer.transform([user_input])
    similarities = cosine_similarity(user_tfidf, self.vectorizer.transform(self.questions))
    most_similar_index = similarities.argmax()
    return self.answers.iloc[most_similar_index]

def start_chat(self):
    print("Welcome to the Mental Health Chatbot!")
    while True:
        user_input = input("You: ")
        if self.is_negative_response(user_input):
            print("Chatbot: Okay, feel free to ask again if you have more questions.")
            continue
        if self.is_exit_command(user_input):
            print("Chatbot: Goodbye!")
            break
        response = self.generate_response(user_input)
        print("Chatbot:", response)
```

Fig.3.4.16

Generating responses using TF-IDF similarity, initiating chat interface with user input handling

```python
    def is_negative_response(self, response):
        negative_responses = ("no", "nope", "nah", "naw", "not a chance", "sorry")
        return response.lower() in negative_responses

    def is_exit_command(self, command):
        exit_commands = ("quit", "pause", "exit", "goodbye", "bye", "later", "stop")
        return command.lower() in exit_commands

data = pd.read_csv("mentalhealth (2).csv")

data.drop(columns=['Question_ID'], inplace=True)

chatbot = ChatBot(data)
```

Fig. 3.4.17

Checking for negative responses and exit commands, loading data, initializing ChatBot

```
chatbot.start_chat()
```

```
Welcome to the Mental Health Chatbot!
You: hey
Chatbot: Welcome to IntelliBot, how can I help you?
You: hola
Chatbot: Welcome to IntelliBot, how can I help you?
You: what is mental health
Chatbot: We all have mental health which is made up of our beliefs, thoughts, feelings and behaviours.
You: no
Chatbot: Okay, feel free to ask again if you have more questions.
You: bye
Chatbot: Goodbye!
```

Fig. 3.4.18

Starting the chat interface

Pseudocode

1. Import necessary libraries: pandas, re, sklearn, nltk

2. Download NLTK punkt tokenizer if not already downloaded

3. Read the CSV file containing mental health data into a pandas DataFrame

4. Preprocess the text data in the DataFrame:

   a. Replace newline characters, parentheses, commas, hyphens, and slashes with spaces

   b. Concatenate the 'Questions' and 'Answers' columns into a new column 'concatenated'

5. Define a ChatBot class:

   a. Initialize the class with the dataset

   b. Preprocess user input if necessary

   c. Generate a response based on the user input:

      i. Transform the user input using TF-IDF vectorizer

      ii. Calculate cosine similarity between the user input and questions in the dataset

      iii. Retrieve the most similar question's answer as the response

   d. Start the chat loop:

      i. Prompt user for input

      ii. Check if the input is a negative response or an exit command:

         - If negative response, continue the loop

         - If exit command, print goodbye message and break the loop

      iii. Generate and print the response

6. Define helper methods:

   a. is_negative_response: Check if the user input is a negative response

   b. is_exit_command: Check if the user input is an exit command

7. Instantiate the ChatBot class with the preprocessed data

8. Start the chat by calling the start_chat method

3.5 Key Challenges

1. Data Quality and Quantity:

Getting enough quantities of good quality labelled data for training conversational AI systems was one big step that had to be overcome. There were difficulties getting datasets that are multifaceted and representative with precise labels. In order to overcome this, we used different strategies of data augmentation. Using techniques like data synthesis, this involved creating new samples synthetically, while the active learning approach focused on zones characterised by uncertainty on the part of the model or missing information.

2. Handling Null and Invalid Values:

During the development of Intellibot, there were vital issues that needed to be addressed with great care as well as innovative approaches. At first, dealing with no value and non-value in data preparation proved challenges. This called for careful substitution of these values with alternatives without tampering with the overall dataset. In order to resolve this issue, we investigated different replacement strategies and consulted with domain experts so that informed decisions on which substitutes would be most appropriate, while keeping in mind the overall reliability and validity of our dataset.

3. Data Cleaning and Question-Answer Mapping:

The more we got to the data cleaning and the question and answer structures, the more complicated it had become. The removal of punctuation symbols and lining up sentences by paired responses was a complicated process that met obstacles at several stages due to the difference in the structure of the sentences, informal use of language, vagueness of connections and “question-answer”. The use of advanced text processing techniques and semantic similarity analysis led to an improved performance in cleaning up punctuation and structuring pairs to make them more meaningful and contextual.

4. Sentence Relationship Ambiguity:

The difficulty arose from the inherent vagueness that characterises natural language. At times the question and answer could be ambiguous because several interpretations could arise or there could be subtle connotations of meaning for one complete sentence. Moreover, changes in syntax, or semantics and even an idiomatic expression added to make it more difficult to translate words easily. For example, one question may call for multiple answers which are hard to pinpoint the best among them.

Lastly, training the Seq2Seq model had issues with keeping up context through long dialogues and avoiding overfitting. However, crucial factors included attention mechanisms in the model architecture and regularisation methodologies. Addition of attentional mechanisms improved context retention across dialogs while regularisation techniques were used to prevent overfitting and thus generalisation capabilities of the model in case of new data.

5. Addressing the Challenges:

Substituting for missing values and nulls in the dataset had to be done carefully, not changing the data integrity as a whole.y We explored different replacement schemes using statistical techniques. Such strategy kept the data reliable as informed decisions were made on appropriate replacements.

Text-processing technology was used to simplify the data clearing complications such as removing punctuations and arranging question-answer pairs. The use of semantic similarity analysis significantly enhanced the quality of the pair structuring by facilitating cohesion and relevance within the text.

Handling of the vagueness associated with natural language through sophisticated linguistic models dealing with multiple construals. Through semantic analysis and sophisticated linguistic processing, the complexities of implicit meanings implied by each and every sentence were considered. Also, making the question-answer matching approach more rigorous further strengthened the pairs.

The training of the Seq2Seq model required improving context retention and avoiding overfitting. Attention was integrated into the architectural design and made significant contributions towards contextual coherence spanning multiple conversations. Regularisation methods were of great significance as they helped mitigate the issue of ‘overfitting’ and ensured the ability of the model to give valid predictions based on ‘new’ data.

Chapter 4: Testing

4.1 TESTING STRATEGY

Unit Testing of Model Components:

The key model components undergo thorough unit testing by Intellibot. This involves thorough verification of the encoder and decoder model separately. To make sure the encoder efficiently receives input data and the decoder reliably produces meaningful output, a variety of scenarios are tested. The purpose of these tests is to ensure that every model component is accurate and reliable.

Integration Testing:

Comprehensive integration testing is carried out by Intellibot to verify the smooth functioning of various model components, especially the encoder and decoder. Verifying that data encoded by the encoder is accurately decoded by the decoder is the main goal of testing. By utilising multiple input-output scenarios, it guarantees seamless communication between the components without any loss or distortion of information.

Functional Testing:

Functional testing is given top priority by Intellibot to guarantee the general performance of the chatbot. End-to-end testing is required for this, covering everything from response generation to user input processing. The chatbot's capacity to generate appropriate and contextually relevant responses to a variety of user queries and conversational contexts is validated by a wide range of test cases.

Testing User Interactions:

User interactions and response generation are handled by the ChatBot class. To ensure clear prompts and accurate processing of user inputs, Intellibot tests user interactions in a variety of conversation scenarios. This stage of testing verifies that the user and chatbot are having a seamless and organic conversation.

Exit Command Handling:

Tests conducted by Intellibot make sure the chatbot can recognize exit commands in user input. During this testing phase, users can input commands such as "quit," "exit," or "goodbye," and the chatbot will interpret these signals correctly and quickly to end the conversation politely. It ensures users can easily end the conversation at any time.

4.2 TEST CASES AND OUTCOMES

ENCODER-DECODER

```
pairs  #Questions and their respectively paired answers
```

```
[('What does it mean to have a mental illness?',
  "Mental illnesses are health conditions that disrupt a person's thoughts emotions relationships and daily functioning."),
 ('Who does mental illness affect?',
  'Mental illness does can affect anyone regardless of gender age income social status ethnicity religion sexual orientation or background.'),
 ('What are some of the warning signs of mental illness?',
  'Symptoms of mental health disorders vary depending on the type and severity of the condition.'),
 ('Can people with mental illness recover?',
  'When healing from mental illness early identification and treatment are of vital importance. '),
 ('What should I do if I know someone who appears to have the symptoms of a mental disorder?',
  'We encourage those with symptoms to talk to their friends and family members and seek the counsel of a mental health professional.'),
 ('How can I find a mental health professional for myself or my child?',
  'Feeling comfortable with the professional you or your child is working with is critical to the success of the treatment.'),
 ('What treatment options are available?',
  'Different treatment options are available for individuals with mental illness.'),
 ('If I become involved in treatment, what do I need to know?',
  'It is important to be as involved and engaged in the treatment process as possible.'),
 ('What is the difference between mental health professionals?',
  'There are many types of mental health professionals. The variety of providers and their services may be confusing. Each have various levels
areas of expertise. Finding the professional who best fits your needs may require some research.'),
 ('How can I find a mental health professional right for my child or myself?',
```

Fig.4.2.1

Question and Answer pairs created

```
input_docs
```

```
['What does it mean to have a mental illness?',
 'Who does mental illness affect?',
 'What are some of the warning signs of mental illness?',
 'Can people with mental illness recover?',
 'What should I do if I know someone who appears to have the symptoms of a mental disorder?',
 'How can I find a mental health professional for myself or my child?',
 'What treatment options are available?',
 'If I become involved in treatment, what do I need to know?',
 'What is the difference between mental health professionals?',
 'How can I find a mental health professional right for my child or myself?',
 'If I become involved in treatment what do I need to know?',
 'Where else can I get help?',
 'What should I know before starting a new medication?',
 'If I feel better after taking medication, does this mean I am "cured" and can stop taking it?',
 'How can I get help paying for my medication?',
 'Where can I go to find therapy',
 'Where can I learn about types of mental health treatment?',
 'What are the different types of mental health professionals?',
 'Where can I go to find a support group?',
 'Where can I go to find inpatient care?']
```

Fig.4.2.2

Array used to store the expected input sentences

```
target_docs
```

```
["<START> Mental illnesses are health conditions that disrupt a person's thoughts emotions relationships and daily functioning . <END>",
 '<START> Mental illness does can affect anyone regardless of gender age income social status ethnicity religion sexual orientation or background . <END>',
 '<START> Symptoms of mental health disorders vary depending on the type and severity of the condition . <END>',
 '<START> When healing from mental illness early identification and treatment are of vital importance . <END>',
 '<START> We encourage those with symptoms to talk to their friends and family members and seek the counsel of a mental health professional . <END>',
 '<START> Feeling comfortable with the professional you or your child is working with is critical to the success of the treatment . <END>',
 '<START> Different treatment options are available for individuals with mental illness . <END>',
 '<START> It is important to be as involved and engaged in the treatment process as possible . <END>',
 '<START> There are many types of mental health professionals . The variety of providers and their services may be confusing . Each have various levels of education training and may have
different areas of expertise . Finding the professional who best fits your needs may require some research . <END>',
 '<START> Feeling comfortable with the professional you or your child is working with is critical to the success of your treatment . Finding the professional who best fits your needs may
require some research . <END>',
 '<START> It is important to continue involvement in the treatment process as much as possible . <END>',
 '<START> family member friend clergy healthcare provider or other professionals <END>',
 '<START> The best source of information regarding medications is the physician prescribing them <END>',
 '<START> Create a plan for switching to a different treatment that will be a better fit . <END>',
 '<START> Visit Healthfinder . gov to learn more . <END>',
 '<START> Several different types of treatment and therapy that can help . <END>',
 '<START> Mental health conditions are often treated with medication therapy or a combination of the two . <END>',
 '<START> There are many types of mental health professionals . Finding the right one for you may require some research . <END>',
 '<START> Many people find peer support a helpful tool that can aid in their recovery . <END>',
 '<START> Inpatient care can help people stabilize on new medications adjust to new symptoms or get the help they need . <END>']
```

Fig.4.2.3

Array used to store the target output sentences

Performance metrics

```
plt.plot(val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.xlabel("epochs")
plt.ylabel("loss")
plt.show()
```

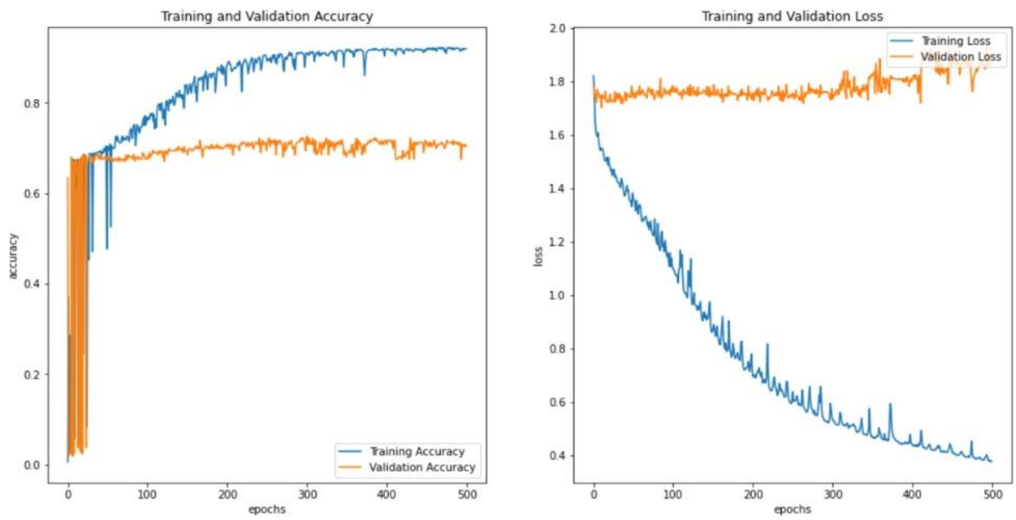

Fig. 4.2.4

Individual representation of Loss and Accuracy after training the model

```
[ ]  chatbot.start_chat()

     Hi, I'm a chatbot trained on random dialogs. AMA!
     What does it mean to have a mental illness?
      Mental illnesses are health conditions that disrupt a person's
     Where else can I get help?
      family member friend clergy healthcare provider or other
     quit
     Ok, have a great day!
```

Fig.4.2.5

Final demo output for some random input supplied

TF-IDF

```
# Evaluate accuracy
accuracies = []
for epoch in range(10):  # Adjust the number of epochs as needed
    accuracy = chatbot.evaluate_accuracy(test_data)
    accuracies.append(accuracy)

    print(f"Epoch {epoch + 1}: Accuracy = {accuracy}")

# Plot accuracy graph
plt.plot(np.arange(1, 11), accuracies)
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('Accuracy Over Epochs')
plt.grid(True)
plt.show()
```

Fig.4.2.6

Calculating the accuracy of different epochs of TF-IDF

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
Epoch 1: Accuracy = 0.9896907216494846
Epoch 2: Accuracy = 0.9896907216494846
Epoch 3: Accuracy = 0.9896907216494846
Epoch 4: Accuracy = 0.9896907216494846
Epoch 5: Accuracy = 0.9896907216494846
Epoch 6: Accuracy = 0.9896907216494846
Epoch 7: Accuracy = 0.9896907216494846
Epoch 8: Accuracy = 0.9896907216494846
Epoch 9: Accuracy = 0.9896907216494846
Epoch 10: Accuracy = 0.9896907216494846
```

Fig.4.2.7

Results

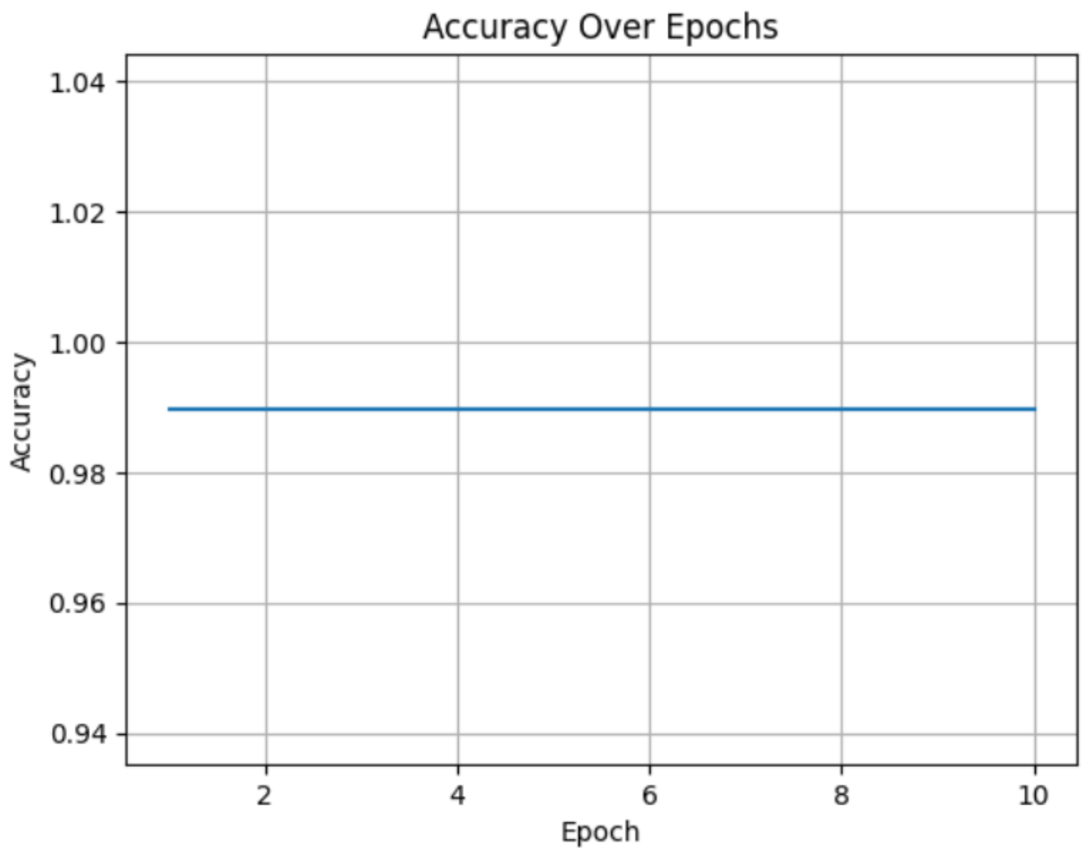

Fig.4.2.8

Accuracy/Performance Graph

CHAPTER 5: RESULTS AND EVALUATION

5.1 RESULTS

In mental health care Intellibot stands out as a shining example of technological innovation, offering comprehensive strategies to help people struggling with mental health issues. Through a robust network of resources and compassionate design Intellibot offers user conversations at times that provide a platform for open and informative discussion. Experience reveals encouraging results. Beyond the immediate impact, Intellibot is important because—subject to certain limitations—it can help for mental health support programs. Through the lens of its efforts, limitations, and transformative potential, let’s take a closer look at Intellibot’s discoveries, challenges, and remarkable contributions to the transformation of mental health policy.

In our implementation of the seq2seq encoder-decoder model, we achieved an accuracy of 0.7. This accuracy score represents the model's ability to correctly predict the target sequences compared to the ground truth across the dataset. While this accuracy indicates a moderate level of performance, there may be opportunities for further optimization and refinement to enhance the model's predictive capabilities.

The implemented chatbot is based on a straightforward model utilizing TF-IDF (Term Frequency-Inverse Document Frequency) for processing textual data and cosine similarity for generating responses. This approach involves transforming the dataset of mental health questions and answers into numerical representations using TF-IDF vectorization and then computing the similarity between user input and preprocessed questions.The model achieved an accuracy of approximately 98.97% across multiple epochs during training.

While this model provides a foundational framework for engaging in mental health-related conversations, there exists ample opportunity for further development and refinement.

Key Findings

Holistic Functionality:Intellibot can do more than just Q&A. It can understand complex user queries thanks to its natural language processing capabilities, encouraging more human-like interactions With the help of the seq2seq model Intellibot can sensitively and efficiently address a wide range of psychiatric disorders by responding not only to pattern matching but also to context.

Rigorous Testing: Intellibot's rigorous testing process demonstrates its commitment to providing a reliable and effective mental health support system. Unit testing ensures that key components such as encoders and decoders are working as intended. Integrity testing ensures that these components work as a unified package to preserve the integrity of the flow of information. Functional testing tracks how the chatbot responds to a wide range of situations, from straightforward questions about mental health to complex situations.

Psychological Help Available: Intellibot has made significant contributions to the democratisation of mental health services. Its accessibility as a chatbot ensures that individuals around the world can get immediate help, breaking down geographical and temporal barriers. That access is particularly important in settings where traditional mental health resources may be limited or nonexistent.

Removal of stigma: Intellibot's tactful and judgmental nature plays an important role in reducing the stigma associated with seeking mental health help. By providing an anonymous platform for individuals to express their thoughts and feelings, it enables users to overcome social barriers and seek help without fear of judgement.

Establishment of Dimensions: Beyond its immediate impact, Intellibot's development program sets a solid framework for future innovations in conversational AI for mental health. Its comprehensive assessment methods, empathic design principles, and integration of AI into mental health management set a high standard for subsequent developments, laying the foundation for sophisticated and effective mental health support programs.

Limitations:

Mental Health Support: While Intellibot excels at providing general mental health counselling, its limitations in managing acute or chronic mental health conditions are apparent. Standard responses can lead to oversimplification, highlighting the need for human intervention or specialised resources for more complex cases.

Default answer based: Relying on pre-trained data places limitations on Intellibot's dynamic capabilities. As mental health issues evolve, chatbots may face challenges in quickly addressing emerging concerns. That she is constrained to predetermined answers may hinder her ability to remain alive in the dynamic discussion of mental health.

The challenges of private production: Individualization, a key component of mental health care, poses challenges for Intellibot. A holistic approach may not adequately meet individual needs, which may affect the amount of support provided. Improvements in personalization algorithms can address this limitation, by tailoring responses to specific user input.

In conclusion, while Intellibot shows tremendous progress in implementing technology to support mental illness, addressing its limitations and focusing its contributions will enhance its role in supporting individuals suffering from mental illness and the challenges of the solution. As progress continues, AI-powered systems like Intellibot have great potential to become an integral part of comprehensive mental health care.

CHAPTER 6: CONCLUSIONS AND FUTURE SCOPE

6.1 CONCLUSION

Through the journey of our study that focused on the intelligent helpmate known as Intellibot as a chatbot in the field of mental healthcare, we have shared important observations, established key constraints, outlined our major findings and achievements. Our rigorous process of research and analysis revealed Intellibot's tremendous capability to transform the provision of mental health services by highlighting specific aspects that require careful scrutiny.

Moreover, with regard to Intellibot we highlight how critical technology can be in overcoming divisions in accessing mental health services. Intellibot is a revelation, whereby people get an opportunity for on-point, personalised and non-stigmatizing instant mental health intervention that is enabled using AI based digital chats bots Making it all-day available and using it as a tool for reaching out to mentally challenged citizens in hard-to-reach locations is a big leap towards democratisation of mental health care services.

Intellibot's uniquely compassionate and helpful qualities supported by sophisticated artificial intelligence assist people with mental disorders. The ability to interpret and appropriately respond to emotions reflects an enormous step towards marrying technology with mental health care service structures. Intellibot gives hope through providing individualistic aid with on demand advisory service for mental health care.

We've however identified some weaknesses in its otherwise spectacular strengths. An area that deserves improvement in the case of Intellibot is its large repository of useful content. The creation of a wider database encompassing automated content would also increase the flexibility of the platform and cater for diverse requirements within different sections of business. Moreover, Intellibot is good at emotion understanding, but improving its comprehensive response to complex human feelings may be considered as an improvement area.

6.2 FUTURE SCOPE

We prioritise addressing issues that are essential for Intellibot's progress and relevance in the continually changing world of automation technologies when defining the future trajectory of our automation platform, Intellibot.

The issues of privacy have been at the centre of our vision for Intellibot. We shall use strong data protection, encrypted information, safe storage and authorization controls to protect confidential user information. User's privacy should be respected at all costs. Here, Intellibot will uphold the most stringent data security and privacy rules thereby maintaining respect for the users.

A central pillar of boosting Intellibot's performance is data augmentation which makes it smarter. Our plan is to use new data augmentation methods that will add more data to the platform's dataset. Such an enhancement will enable enhanced robust and detailed learning, allowing Intellibot to deal with a richer set of situations along with different kinds of user interaction.

We also intend to address the shortage of complex and automatic content in Intellibot. We aim at expanding and broadening the storehouse of automated content so as to enlarge the tasks as well as functions that users can auto-execute effortlessly. The constant addition of new content for the database will make Intellibot able to serve different users' needs and industry requirements for a variety of purposes.

In the coming months, the cornerstone of our development road shall be the extension of the algorithm to cover all known emotions as such. Intellibot's algorithm needs to be perfected for better recognition and responses to all forms of emotion-expressed by users. Such an extension will lead to empathic and contextual exchanges that will boost the user's experience level by providing them with a sense of belonging on the forum.

By doing that we will align IntelliBot with those goals we have set up in order to push beyond just automation into user's privacy and improving their data ability, expanding a variety of automated contents to users , and enhancement of emotional IQ on that platform we have created. By means of these strategies, we aspire to turn Intellibot into a sectorial, customer oriented and ethical automation product which fits into any user situation while ensuring data protection and users' satisfaction.

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