GROUP 5 : Emotional Health Chatbot: Project Report

Submitted in partial fulfilment of EBA5004 Practical Language Processing: Practice Project

Project GitHub Link: https://github.com/PLPWork/Emotional_Health_Expert
Project Demo Video: https://www.youtube.com/watch?v=2iqxXFh1QL4

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1 Abstract

Anxiety and depression rates are at an all-time high. Smartphone based mental health chatbots can aid psychiatrists and specialists replacing some of the costly human based interaction providing a unique opportunity to expand the availability and quality of mental health intervention whilst providing an alternative elective approach to fill the much-needed self-care gap.

The Family of mental issues in not small, as they come in a group :-

Stress	Eating Disorders	Self-Esteem Issues	Disgust	Social Isolation	Loneliness
Anxiety	Mood Disorders	Self-Harm & Anger	Postpartum Anxiety	Trauma	Grief & Loss
Depression	Obsessive Compulsive Disorders (OCD)	Depressive & Bipolar Disorders	Schizophren ia	PTSD	Suicide

And hence they need special care and assistance at different stages or recovery.

Forgiveness	Sleep	Meditation	Nutrition & Exercise	Counselling & therapy
Resiliency	Society & Communication	Healthy Relationships	Self-Care	CBT/DBT/MI

2 Introduction

2.1 Background

According to the World Health Organization , there is a global shortage of health workers trained in mental health. Many mental health interventions do not reach those in need, with approximately 70% with no access to these services.
In the United States alone, 42.6% of adults with mental illness received mental health services in 2017. More specifically, in primary care settings, 75% of patients with depression have one or more structural or psychological barriers that interfere with access to behavioural treatments.
Role of Technology: To address these challenges, we need new models of delivering psychosocial interventions. It was suggested that behavioural intervention technologies (BITs) offer a potential solution to overcome barriers that prevent access and expand mental health care.
BITs are the application of behavioural and psychological intervention strategies through the use of technology features that address behavioural, cognitive, and affective components that support physical, behavioural, and mental health . BITs, such as internet interventions for anxiety and depression, have empirical support with outcomes similar to therapist-delivered cognitive behavioural therapy (CBT). Several BITs involve the same content as face-to-face CBT programs that allow them to reach larger numbers of people at lower costs .

Chatbots represent a particular type of BIT to address mental health conditions. Chatbots are computer programs that engage in text-based or voice-activated conversations and that respond to users based on pre-programmed responses or artificial intelligence (AI). It was found that interactions with chatbots were as effective as human interactions in offering emotional, relational, and psychological benefits and that they focused on the impact of personal disclosure.

Chatbots might be a scalable solution that gives an interactive means of engaging users in behavioural health interventions driven by AI. Although some chatbots have shown promising early efficacy results, there's limited information about how people use these chatbots. Understanding the usage patterns of chatbots for depression represents an important step toward improving chatbot design and providing information about the strengths and limitations of chatbots.

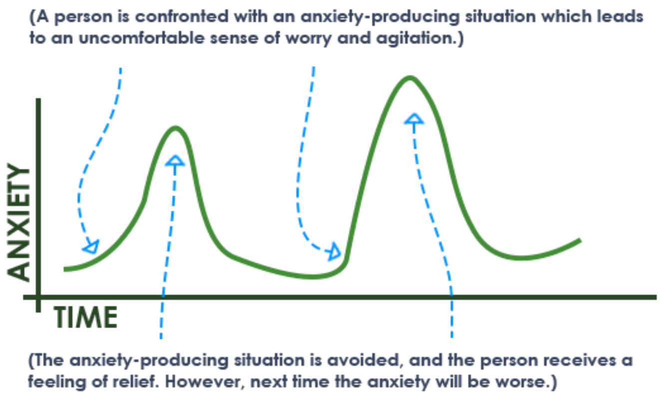
3 Literature Review and Related work

3.1 Domain Concepts

3.1.1 Stress / Anxiety / Loneliness

Stress, anxiety and loneliness levels have reached an all-time high, with nearly half of U.S. adults reporting they sometimes or always feel alone. It is reported they sometimes or always feel that their relationships are not meaningful and that they feel isolated. There is robust evidence that social isolation and loneliness significantly increase risk for premature mortality, and the magnitude of the risk exceeds that of many leading health indicators.

Anxiety is a feeling of intense discomfort, which drives people to avoid the feared stimuli. Below diagram shows how Anxiety is defined by avoidance and thereafter it returns with increased impact (unless treated well) -

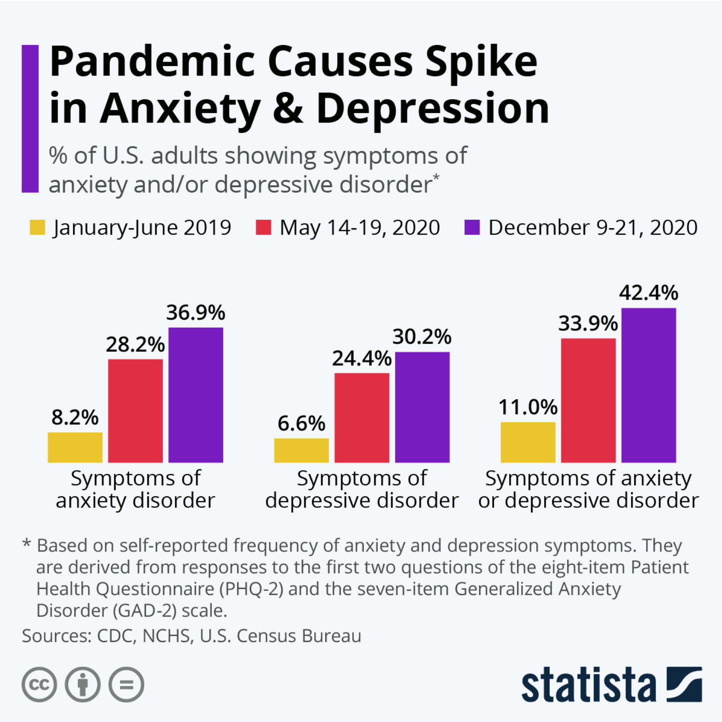


i. **Yerkes-Dodson law** can help a victim to understand why they have anxiety, how it is hurting them, and how a certain amount of anxiety can be beneficial.

3.1.2 Depression / Suicide

Sadness, feeling down, and having a loss of interest or pleasure in daily activities are familiar feelings for all of us. But if they persist and affect our lives substantially, the issue may be depression.
Depression is the main cause of disability and suicide worldwide, according to the World Health Organization (WHO). It can affect adults, adolescents, and children.

Recently with COVID-19 pandemic there is a spike in anxiety and depression. Within Singapore itself we have seen Sucide cases highest in 8 years (452 cases in 2020 alone).



3.2 Issues Inducers

There is wide range of reasons behind the depression like time at college can stressful, and a person may be dealing with other lifestyles, cultures, and experiences for the first time. Physical changes, peer pressure, and other factors can contribute to depression in teenagers. Younger children may have difficulty expressing how they feel in words. This can make it harder for them to explain their feelings of sadness. Hence a chatbot will be a good tool to reach out to such users.

b. Available Matrix

Quantitative assessment of the intensity of depression is an important step towards reflection of the state of the victim and accordingly the right level assistence and treatment can be provided. We have explored few options especially to design our survey question and shiortlisted HADS scale for the final implementation. Below are the details of couple of scales available for the purpose -

Beck's Depression Inventory
The Beck Depression Inventory (BDI) is a 21-item, self-report rating inventory that measures characteristic attitudes and symptoms of depression (Beck, et al., 1961). The BDI demonstrates high internal consistency, with alpha coefficients of .86 and .81 for psychiatric and non-psychiatric populations respectively.

The development of the BDI was an important event in psychiatry and psychology. it represented a shift in health care professionals' view of depression from a Freudian, psychodynamic perspective, to one guided by the patient's own thoughts or "cognition".

It also established the principle that instead of attempting to develop a psychometric tool based on a possibly invalid theory, self-report questionnaires when analysed using techniques such as factor analysis can suggest theoretical constructs.

The Hospital Anxiety and Depression Scale (HADS) was devised 30 years ago by Zigmond and Snaith to measure anxiety and depression in a general medical population of patients. The beauty of the HADS score is its simplicity, speed and ease of use. Very few (literate) people have difficulty completing it, on paper or electronically. It assesses both anxiety and depression, which commonly coexist.
Anxiety is poorly recognized by clinicians, so should be actively sought. Anxiety often precedes depression in response to stressors and identifying the employee with high or rising anxiety before depression allows occupational health practitioners to advise on early intervention measures

Hospital Anxiety and Depression Scale (HADS)

Tick the box beside the reply that is closest to how you have been feeling in the past week.
Don't take too long over you replies: your immediate is best.

D	A		D	A	
		I feel tense or 'wound up':			**I feel as if I am slowed down:**
	3	Most of the time	3		Nearly all the time
	2	A lot of the time	2		Very often
	1	From time to time, occasionally	1		Sometimes
	0	Not at all	0		Not at all

HADS Scoring

Total score:

- Depression (D) ___________
- Anxiety (A) ______________

1) 0-7 = Normal
2) 8-10 = Borderline abnormal (borderline case)
3) 11-21 = Abnormal (case)

3.3 Existing solutions

Progressively, online media is being utilized for breaking down social qualities for medical care like data about illnesses in light of Twitter posts. Social media platforms like Twitter are broken down to do a feeling investigation distinguish despondency characteristics in clients. Rather than thinking about the conducting angle, information from online media is additionally taken up as a text order issue to recognize gloom. This undertaking utilizes information of text and discourse to distinguish and break down the reason for depression.

In this review, mental health-related apps, that incorporate chatbots or conversational agents particularly for anxiety and depression, were outlined. These include apps available on Google Play Store (Android) and Apple Store. However, some of these chatbots also targeted other mental health issues such as sleep and stress.

A total of 11 chatbot containing apps were included in this review collected from the Google Play and Apple Store in which (6/11) were related to health and fitness whilst (5/11) were medical-related apps. The main self-help (management) interventions focused on in this review include mindfulness, mood tracking, meditation, and functional assessments. The most common mental conditions amongst the chatbot apps were anxiety and depression (9/11) and (8/11), respectively, in line with our search strategy. The most common management approach amongst the apps was mindfulness (7/11).

Moreover, the study observed some general characteristics of mental health apps in Table 4 and only included apps with rating 4+ in this review in an attempt to not include lowly rated apps. The app Mindspa received the highest rating (4.9/5), however, with fewer installations (100, 000+) compared to some of the others. This could be down to the fact it is completely free of charge therefore with less funding revenue. The mindsspa app contains an emergency reporting based chatbot feature helping individuals with anxiety and depression as opposed to the personalized avatar style bots seen in some of the other apps. The targeted age group of the majority of the apps reviewed was 12 years and above, outlining possible additional challenges faced when providing such services to children.

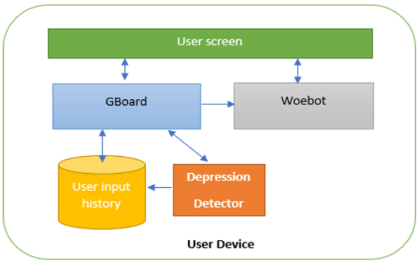
Shneidman presented depression that tended to be closely related to suicide. De Choudhury et al analyzed Reddit users' posts on the topic of mental health that later turned to the topic of suicidal thoughts. This turn could be predicted by traits such as self-focus, poor language style, reduced social engagement, and expressions of despair or anxiety. Yates et al proposed a neural framework for depression detection, and they presented that self-harm was closely related to depression. The Conference and Labs of Evaluation Forum for Early Risk Prediction (CLEF eRISK) is a public competition about different areas such as health and safety CLEF eRISK 2018 is about the early detection of depression and anorexia.CLEF eRISK 2019 is about the severity of symptoms of depression, self-injury, and anorexia Different from traditional feature engineering-based methods, deep learning methods mostly apply end-to-end models. Yates et al proposed a neural framework based on a CNN for depression detection. Orabi et al proposed a neural method based on CNN and RNN for depression detection. Song et al proposed a neural network that was named the feature attention network for depression detection. Gui et al proposed a reinforcement learning method based on long short-term memory (LSTM) for depression detection. Ray et al proposed a multilevel attention network to fuse the features from the multimodal for depression detection.

Right now, most examination depends on determination and advancement, and restricted overviews work on subjects and feelings that these are next to no sum patients who express their sentiments on friendly stages, only in web-based well being networks (OHC). Various strategies were used to find that in the number of classifications the opinions are separated, following procedures were utilized Latent Dirichlet, Naive Bayes calculations and Concept Frequency-Inverse report recurrence, with the assistance of a device named Gephi instrument, used to examine the development in the public eye, with the assistance of feeling investigation healthcare care experts says they improve understanding between tolerant experience and needs, yet this work is done on a limited scale.

Some list of chatbots:

- **Joyable, Talksapce, Woebot** for monitoring health system.
- AI platforms like **Wysa** and **Woebot** are comprehensive, professional-quality chatbots but some reviews mention about lack of commitment on some blogs. They also lack reach out factor for the depressed people.
- **Joyable** provides mental health coaches and Talkspace provides licensed health professionals.

An example of design fundamentals can be seen below for Woebot. We have taken it further to the next stage.



1 Technology Options/Method

1.1 Design Goals of solution

Our design goal is tied in with making a chatbot that gives human-like reactions to the text entered by the client. These reactions are redone to a client and contain articles or chats which help to investigate and address the explanation of sorrow in the user. The user can rate the articles on how supportive they tracked it down. This rating would be utilized by the application for additional articles or music suggestions. The objective of this undertaking is that the users should feel open to sharing their concerns on the application to connect with those confronting discouragement, however, they can't manage the cost of clinical benefits or are hesitant to look for treatment. Depression and loneliness go untreated as a rule, which can bring about suicides. This application gives the client where they can share any issues they confront and get help or a wellspring of inspiration, which can end up being extremely useful for certain cases. Albeit this application is intended for discouraged patients, it tends to be utilized by anybody as a medium to share issues and get inspiration on troublesome occasions.

1.2 Social Media Platforms

1.2.1 Twitter

Twitter – one of the most famous informal communication or 'miniature publishing content to a blog' destinations – separates itself as a wellspring of literary information by availability and sheer volume. Practically every type of effort on Twitter is public as a matter of course, and its clients basically broadcast their messages to whoever needs to tune in. This transparency yields a colossal wellspring of information – about ninety million tweets each day – that analysts have rushed to gain by. Each tweet is a short 140 person message posted by a person. Twitter's Application Programming Interfaces (APIs) take into consideration continuous checking, so it is feasible to follow designs over the long haul with exceptionally low idleness. Just a negligible part of tweets (<1%) contain geo-area information, yet it is feasible to (generally) find tweets utilizing data from the banner's profile. The examples of following, answering to and in any case drawing in with accounts shapes an informal organization of sorts that can be mined notwithstanding Twitter's printed, transient and topographical highlights.

1.2.2 Reddit

The RSDD (**Reddit** Self-reported Depression Diagnosis) dataset consists of Reddit posts for approximately 9,000 users who have claimed to have been diagnosed with depression ("diagnosed users") and approximately 107,000 matched control users. All posts made to mental health-related subreddits or containing keywords related to depression were removed from the diagnosed users' data; control users' data do not contain such posts due to the selection process.

1.3 ChatBot Interfaces

1.3.1 Telegram

Telegram Groups are feature-rich by default. We hand-picked Telegram bots that can extend basic chat functionality and make can be easily managed and even supports web interface. With the help of the bot, we can Send a welcome message to every new user. Telegram also supports some advanced features like protect your group from virus/malware link, filter unwanted content (specific links, video, voice messages, etc.) or making our group paid for advanced systems.

1.3.2 Stream Lit

Streamlit is an open-source python framework for building web apps for Machine Learning and Data Science. We can instantly develop web apps and deploy them easily using Streamlit. Streamlit allows you to write an app the same way you write a python code. Streamlit makes it seamless to work on the interactive loop of coding and viewing results in the web app.

2 Manual Data Collection Methods

2.1 Self-data collection and Annotation

Data Collection

Twin-Used twins to collect and scrape data

The time period of our data collection was around 2 weeks

Keywords that we used-depressed, anxiety, lonely, loneliness, sad, depression, anxious, suicidal, lost, using which we collected similar data from online search.

Annotation:

Hence we manually annotated 4 of us in the group divided the data and manually annotated it in case of issues the annotation decided by the majority will sustain.

Used this dataset as seed dataset and classified on unseen data basically using semi-supervised approach to get more data.
Our Final data had 10,000 rows.

The below images shows the data collection and manual annotation:

```
import twint
import nest_asyncio
nest_asyncio.apply()

c = twint.Config()
c.Search = "depressed"
c.Store_json=True
c.Output="demo.json"

twint.run.Search(c)
```

```
1441694872646324224 2021-09-25 09:23:37 +0000 <ap0llo14> don’t even bother putting me in your private story if all you’re gonn
a post is “when you’re sad” “when you’re so depressed 😔❤️🙏” and post you crying all the time. like shut the fuck up honestl
y.
1441694739531587587 2021-09-25 09:23:05 +0000 <Drea7x> Making plans sucks when people are no shows, no answers, or only talk a
bout plans but never go through w/ em or try to make any. I wish everyone wanted company as much as I did 😔❤️ ugh I’m depress
ed. Fuck.
1441694628260896778 2021-09-25 09:22:39 +0000 <elyshevva> woke up alone and depressed ✨⭐❤️✨🌸⭐
1441694577828630534 2021-09-25 09:22:27 +0000 <becktdennis> Jom ah balik,makin lama dekat sini makin depressed aku tengok oran
g bercinta. Mencik aaaaahhhhh 😫😫😫
1441694469913554945 2021-09-25 09:22:01 +0000 <HonElishaDr> Men,  Don't feel harassed, useless or pity yourself, depressed of
```

2.2 Public Data Set:

Distress analysis Interview Corpus(DAIC-WOZ) database

This database is part of a larger corpus, the Distress Analysis Interview Corpus (DAIC) (Gratch et al.,2014), that contains clinical interviews designed to support the diagnosis of psychological distress conditions such as anxiety, depression, and post-traumatic stress disorder

Sentiment 140

This is the sentiment140 dataset. It contains 1,600,000 tweets extracted using the twitter api . The tweets have been annotated (0 = negative, 4 = positive
Transcripts found online that are interviews between a counsellor and a patient

3 Solution Design and Implementation

3.1 System Architecture

The data sources for user interaction comes from Reddit, Twitter and our chatbot which are feeders to our design. The standard data processing is applied and fed from data collection layer to our pipeline.

The pipeline is in 2 pipelines:

Thought Analysis Pipeline:

Here we are listening to the tweets and analysing live tweets or comments and posts and tracking and classifying this post in 4 parts Anxious, Depressed, Lonely and Suicidal. There are two pipelines classic NLP:

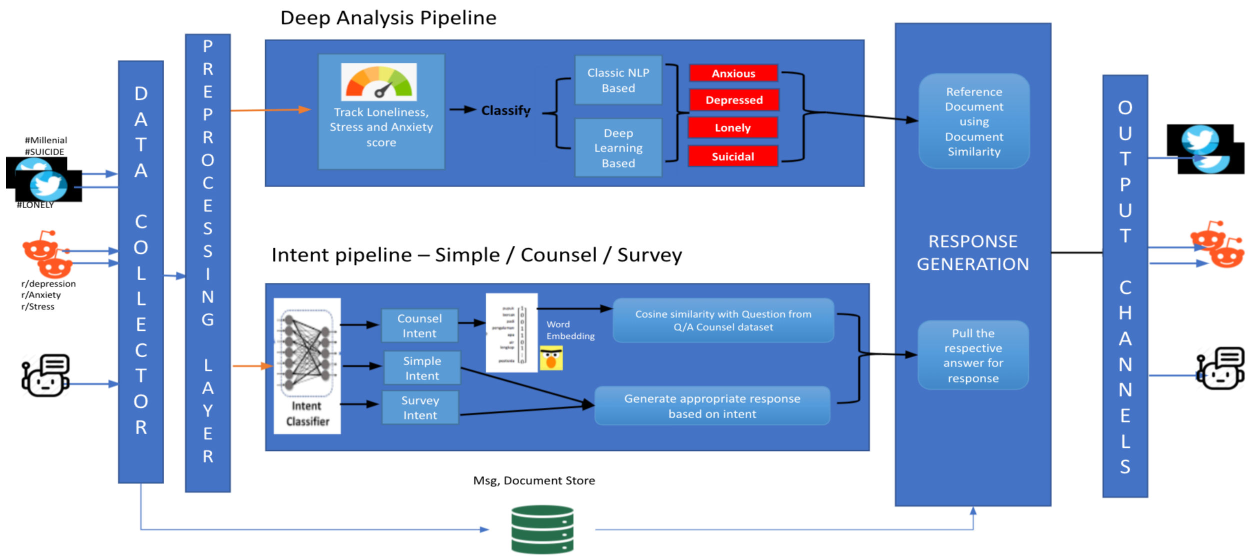
a) First using tf-idf and count vectorizer transformer using NLTK and classification Naïve-Bayesian, Logistic regression and SVM

```
nb = Pipeline([('vect', CountVectorizer()),
          ('tfidf', TfidfTransformer()),
          ('clf', MultinomialNB()),
         ])
```

b) Deep Learning using BERT is used as well where we cross trained BERT with our sentence which are elaborated in upcoming sections.

```
with tf.io.gfile.GFile(bert_config_file, "r") as reader:
   bc = StockBertConfig.from_json_string(reader.read())
   bert_params = map_stock_config_to_params(bc)
   bert_params.adapter_size = None
   bert = BertModelLayer.from_params(bert_params, name="bert")

 input_ids = keras.layers.Input(shape=(max_seq_len, ), dtype='int32',
name="input_ids")
 bert_output = bert(input_ids)

 print("bert shape", bert_output.shape)

 cls_out = keras.layers.Lambda(lambda seq: seq[:, 0, :])(bert_output)
 cls_out = keras.layers.Dropout(0.5)(cls_out)
 logits = keras.layers.Dense(units=768, activation="tanh")(cls_out)
 logits = keras.layers.Dropout(0.5)(logits)
 logits = keras.layers.Dense(units=len(classes), activation="softmax")(logits)

 model = keras.Model(inputs=input_ids, outputs=logits)
 model.build(input_shape=(None, max_seq_len))

 load_stock_weights(bert, bert_ckpt_file)
```

We use document similarity hence and then the response generator will post our chatbot URL on the Twitter, Reddit via their API to the user if it identifies the user in one of the categories as shown below.



<u>Chatbot Interface with Intent classification & response generation pipeline:</u>

Here the user starts interaction with our chatbot and hence the user chats are again fed into por data pre-processing layer for grammatical checks and cleaning and fed into system for intent classification .

There are multiple types of intents and respective dialog states to handle the conversations:

1. <u>Simple Intent</u> (Greeting): Where the user says, hi , Hello etc and is the beginning of chat.
2. <u>Survey Intent</u> (Questionnaire): Here the user wants to proceed with info on a topic like depression so chatbot gives a set of questionnaire to know more about the user situation.
3. <u>Counsel Intent</u> (Q/A Part 1): The intent where user needs help on a specific counsel question and hence chatbot triggers itself.
4. <u>Knowledge Intent</u> (Q/A Part 2): The intent where user needs help on a broader question and hence chatbot triggers itself into a document knowledge base to extract the answer. This also summarizes long ans and provides useful documents to the user for help
5. <u>Ending Intent</u> (Goodbye): Where the user says, bye, end or does not respond for a while etc and is the end of chat.

The entire model hence pulls response for the user and the interaction keeps going on where in our ML model gets Q&A for the user based on exiting corpus of data which we have collected. (The answers and response are based on mining tasks as elaborated in section 6.2)

The models involves BERT, Cosine Similarity, Tf-IDF, Glove, document search and Doc2Vec etc.

1.1 Thought Analysis Pipeline (TAP)

Data Extraction and Pre-processing:

We scratched information for every disease utilizing the Tweepy Programming interface, in view of catchphrases and expressions for every classification. Furthermore, we scratched tweets that didn't contain these watchwords. This information went about as the 'unbiased' information. The information was cleaned utilizing libraries like regex, NLTK. Connections, emoticons, emojis, and images were eliminated.

Deep learning Model:

We used Transformer models and found that BERT(Bidirectional Encoder Portrayals from Transformers) was more qualified for opinion examination. We utilized a pretrained BERT model and tweaked it on our preparation information. We prepared a model for each class. Seaborn to show the level of Depression, Stress, and Tension for every user across time, consequently empowering us to perceive how the client's psychological state differed after some time. In addition, we gauge the weighted normal for every classification, over past tweets

1.2 Mining tasks:

1.2.1 Text classification

Chatbots, or "text informing based conversational specialists", have gotten specific consideration in 2010s. Numerous advanced text-based chatbots utilize generally straightforward NLP devices, or stay away from ML/NLP through and through, depending on the conversation. Here chatbot text classifiers can automatically analyze user tweets and chatbot responses and then assign a set of pre-defined tags or categories based on its content.

<u>Usage in the Project</u> –

- Classify Tweets into different labels i.e. <u>depression, anxiety, stress and loneliness</u> and put a <u>relative score</u> on the prediction of each of these labels.
- User-provided questionnaire information helps to generate labels that survey basis of shortlisting the reference documents that are suitable

1.2.2 Information extraction

Information extraction is the process of extracting specific (pre-specified) information from textual sources hence we have collected a corpus and BOW model for documents related to depression and health. One example is when we email extracts only the data from the document related to suicide in a document.

<u>Usage in the Project</u> –

- <u>When Counsel intent is unable to answer a question</u> then Answer is extracted from Knowledge base documents using BERT Q/A module

1.2.3 Text summarisation

Extractive methods are used in an attempt to summarize articles by selecting a subset of words that retain the most important points. This approach weights the important part of sentences and uses the same to form the summary. Different algorithm and techniques are used to define weights for the sentences and further rank them based on importance and similarity among each other.

Input document → sentences similarity → weight sentences → select sentences with higher rank.

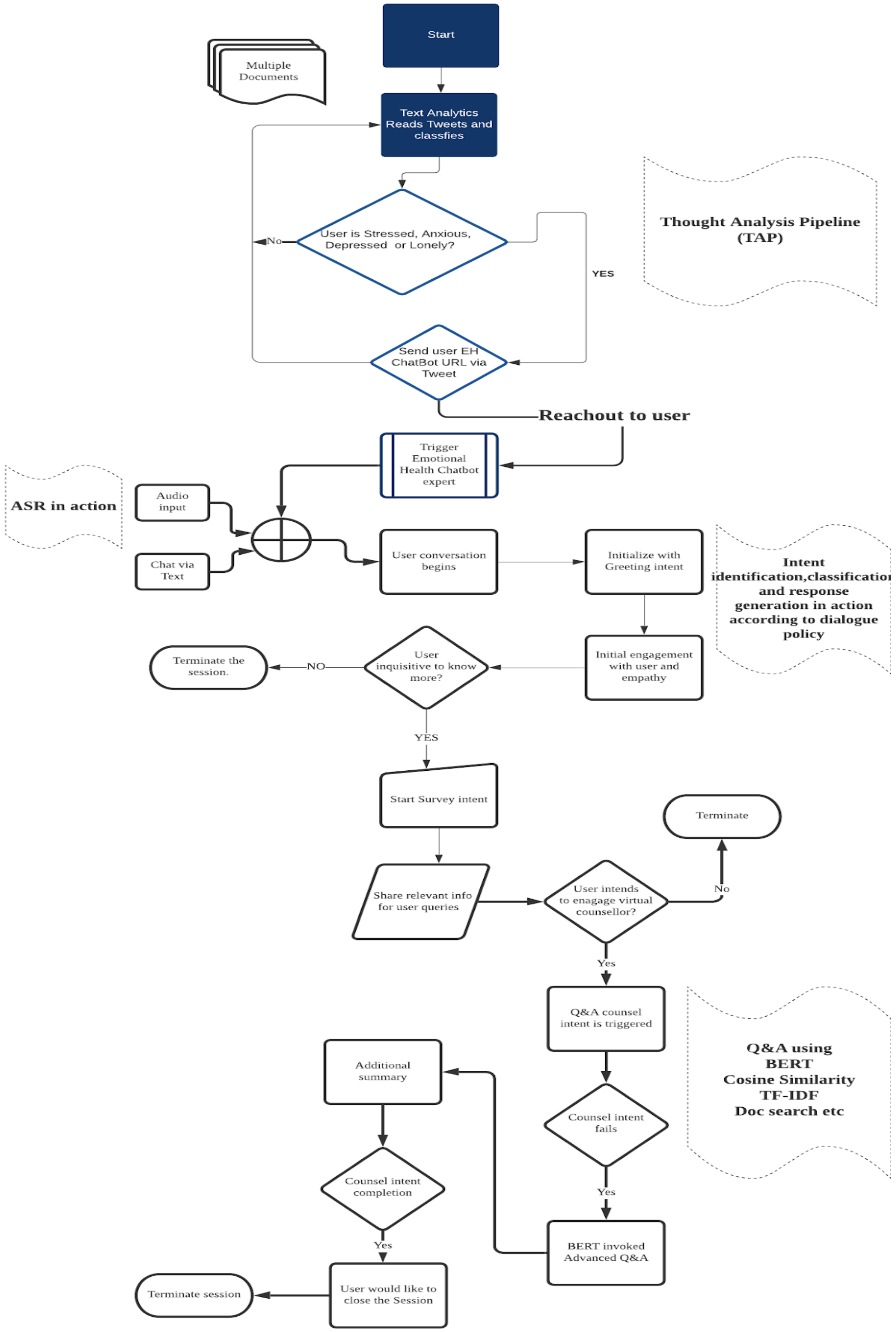
Usage in the Project –

- Text Summarization is used when an extracted answer is longer than the set threshold then the chatbot tries to summarize the answer in Counsel and Knowledge Q/A use cases.

```
legramBot-PizzaOrderBot-master > Summarizer_new.py > ...

from summarizer import Summarizer
from pprint import pprint

with open("C:/Users/verma/Downloads/TelegramBot--master/TelegramBot--master/Depression.txt", 'r',encoding='utf-8') as file:
    data = file.read().replace('\n', '')



data = data.replace("\ufeff", "")

data[0:100]

model = Summarizer()



result = model(data, num_sentences=5, min_length=60)

```

```
2021-11-17 17:46:13.452083: I tensorflow/stream_executor/cuda/cudart_stub.cc:29] Ignore a
('What Is Depression?Depression (major depressive disorder) is a common and '
 'serious medical illness that negatively affects how you feel, the way you '
 'think and how you act. They are also different in important ways:In grief, '
 'painful feelings come in waves, often intermixed with positive memories of '
 'the deceased. In major depression, feelings of worthlessness and '
 'self-loathing are common. When grief and depression co-occur, the grief is '
 'more severe and lasts longer than grief without depression. Before a '
 'diagnosis or treatment, a health professional should conduct a thorough '
 'diagnostic evaluation, including an interview and a physical examination. '
 'For this reason, antidepressants might be prescribed to help modify one’s '
 'brain chemistry.')
```

1.2.4 End to End Flow Diagram



1.2.5 Intent Recognition with BERT

We used Keras and Tensorflow for intent training. Model used was `uncased_L-12_H-768_A-12/` for this training with augmented dataset.

The model is as shown below:

```
def create_model(max_seq_len, bert_ckpt_file):

  with tf.io.gfile.GFile(bert_config_file, "r") as reader:
      bc = StockBertConfig.from_json_string(reader.read())
      bert_params = map_stock_config_to_params(bc)
      bert_params.adapter_size = None
      bert = BertModelLayer.from_params(bert_params, name="bert")

  input_ids = keras.layers.Input(shape=(max_seq_len, ), dtype='int32', name="input_ids")
  bert_output = bert(input_ids)

  print("bert shape", bert_output.shape)

  cls_out = keras.layers.Lambda(lambda seq: seq[:, 0, :])(bert_output)
  cls_out = keras.layers.Dropout(0.5)(cls_out)
  logits = keras.layers.Dense(units=768, activation="tanh")(cls_out)
  logits = keras.layers.Dropout(0.5)(logits)
  logits = keras.layers.Dense(units=len(classes), activation="softmax")(logits)

  model = keras.Model(inputs=input_ids, outputs=logits)
  model.build(input_shape=(None, max_seq_len))

  load_stock_weights(bert, bert_ckpt_file)
```

1.3 Data Exploration

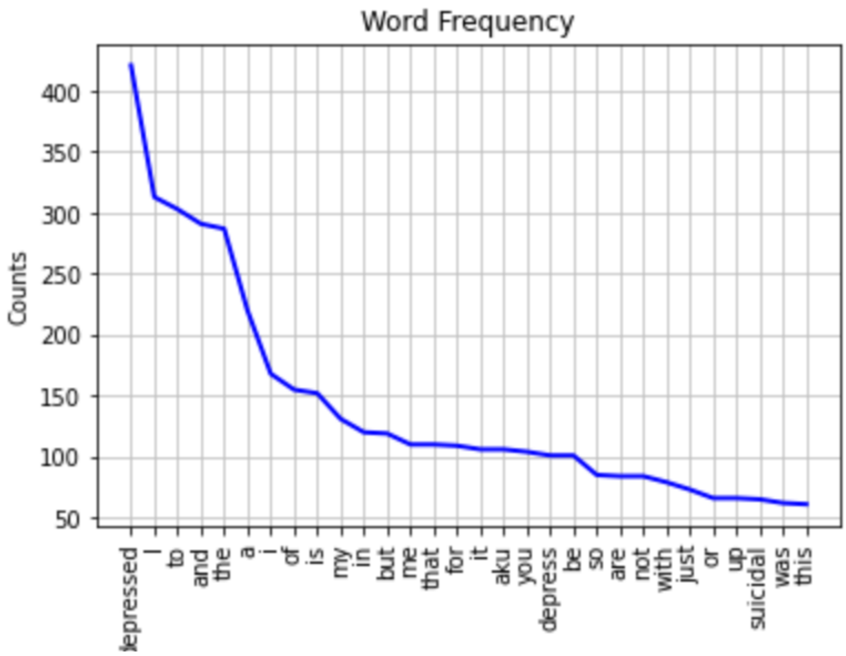
1.3.1 Data Dictionary

Our data dictionary consists of given format:

- **Tweet_id**: The unique ID for this tweet
- **Author_id**: The unique ID for this tweet author (anonymized for non-company users)
- **Created**_at: When the tweet was created
- **Text**: The text content of the tweet
- **Response_tweet_id**: The tweet that responded to this one, if any
- **In_response_to_tweet_id**: The tweet this tweet was in response to, if any

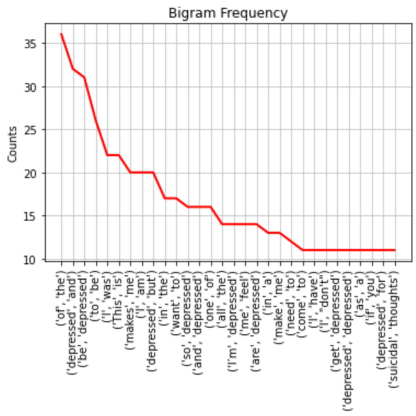
1.3.2 Word frequency

We generated the word count for our entire dataset and mapped the count with depressed being on highest.



1.3.3 Bigrams

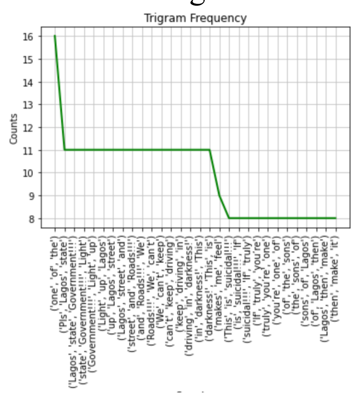
Further data exploration we had to extract the words appearing together the most . Beginning by flattening the list of bigrams. We can then create the counter and query the top 20 most common bigrams across the tweets.




```
Collocation = BigramCollocationFinder.from_wor
Collocation.nbest(bigram.pmi, 20)

[('!!!!', 'Moving'),
 ('")', '@LFCTransferRoom'),
 ('"..."', 'https://t.co/ettua58TTM'),
 ('"Your', 'obv'),
 ('"depress"', 'la,'),
 ('"hati', 'kecilku".'),
 ('"sepi"', 'la..'),
 ('#3titik', 'Buat'),
 ('#FMTNews', 'https://t.co/iynsUAKMKx'),
 ('#FPL', 'Random'),
 ('#JISUNG', '#ParkJinYoung'),
 ('#JungkookBirthday', '@DailyChan_'),
 ('#KerajaaanGagal', '#LAWAN'),
 ('#LAWAN', '#KeluarDanLawan'),
 ('#ParkJinYoung', 'https://t.co/bEObd3jogY'),
 ('#SabahChats', '"mama'),
 ('#TheDevilJudge', '#TheDevilJudgeFinale'),
 ('#TheDevilJudgeFinale', '#JISUNG'),
 ('#UkraineKoyak', '@GSCinemas'),
 ('#experience', '#help')]
```

1.3.4 Trigrams

We even extracted trigrams for most frequent trigrams for data.




```
[('!!!!', 'Moving', 'forward'),
 ('"..."', 'https://t.co/ettua58TTM', "you'll"),
 ('"Your', 'obv', 'depressed"'),
 ('"depress"', 'la,', '"sepi"'),
 ('"hati', 'kecilku".', 'Sia'),
 ('"sepi"', 'la..', 'Pun'),
 ('#FPL', 'Random', 'update'),
 ('#JISUNG', '#ParkJinYoung', 'https://t.co/bEObd3jogY'),
 ('#KerajaaanGagal', '#LAWAN', '#KeluarDanLawan'),
 ('#TheDevilJudge', '#TheDevilJudgeFinale', '#JISUNG'),
 ('#TheDevilJudgeFinale', '#JISUNG', '#ParkJinYoung'),
 ('#experience', '#help', '#thought'),
 ('#help', '#thought', '#reminder'),
 ('#jealous', '#wearisome', '#stressed'),
 ('#mindthinkin', '#jealous', '#wearisome'),
 ('#mypoem', '#mindthinkin', '#jealous'),
 ('#reach', '#remember', '#understand'),
 ('#reachout', '#needhelp', 'https://t.co/ae4WuxwuCq'),
 ('#remember', '#understand', '#understanding'),
 ('#reminder', '#reachout', '#needhelp'),
```

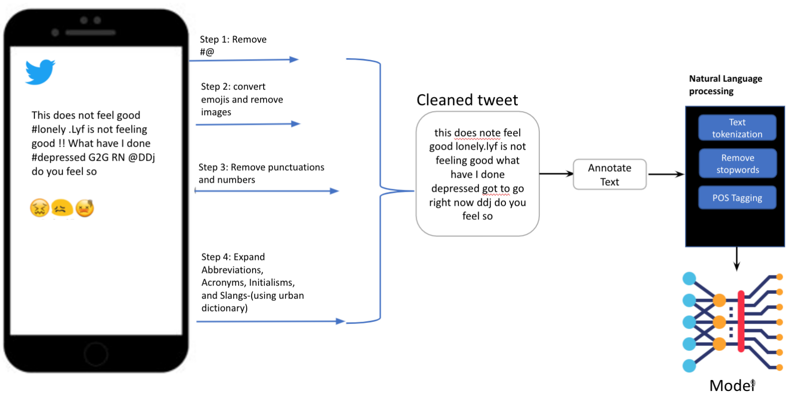
1.3.5 Word cloud mapping

The map of word cloud was generated using `wordcloud` and plotted via matplotlib.

After our analysis depressed suicidal, life , feel etc are the words where we can see higher in frequency for the training.

1.4 Data/Text processing pipeline

We had to find data that best covers as many scenarios that the users might ask chatbot and that we want to reply to as possible. The data should contain all the intents we want to be able to answer. This was a very hard task, but and it came from multiple sources but we focussed as long as they are within the same general domain we can use it.
For each intent, we should have a sizable amount of examples so that our bot will be able to learn the nature of that intent.



Standard data processing pipelines were applied by us which included below steps:

- Converting to lower case
- Tokenizing using NLTK's Tweet tokenizer
- Removing punctuation and URL links as URLs were not needed
- Correcting misspellings (leviathans distance)
- Removal of the stop words
- Removing non-english Tweets with spaCy
- Lemmatization was done instead of stemming as we wanted to focus on context of the data.
- Keeping emojis and to do emoji analysis was an important part as it was an expression of user's state of mind.
- Limiting each Tweet length to 50 so it's comprehendible by system.

We compiled all this steps functions. At every preprocessing step, we can visualize the lengths of each tokens at the data. We also provide a peek to the head of the data at each step so that it clearly shows what processing is being done at each step.

1.4.1 Emoji analysis

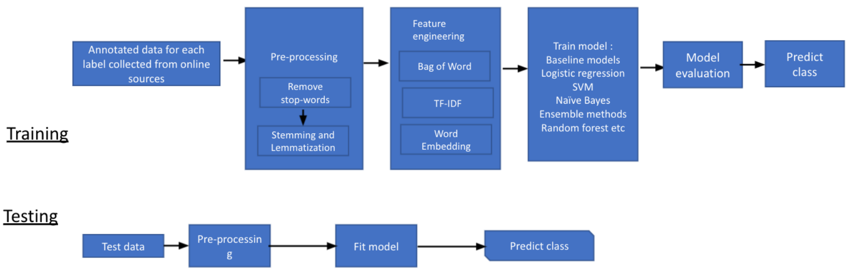
We converted emoji's as suggested for processing the user's view as it determines the user state of mind. So it was included .

```
text = tweets_data['tweet_lower']
for row in text:
    text = demoji.findall(row)
    print(text)
```

```
{'😅': 'grinning face with sweat'}
{}
{'😔': 'pensive face'}
{}
{}
{}
{}
{}
{}
{}
{}
{}
{}
{}
{'😭': 'loudly crying face', '🥺': 'pleading face'}
{}
{}
{}
{'😂': 'face with tears of joy'}
{'😔': 'pensive face'}
{}
{}
```

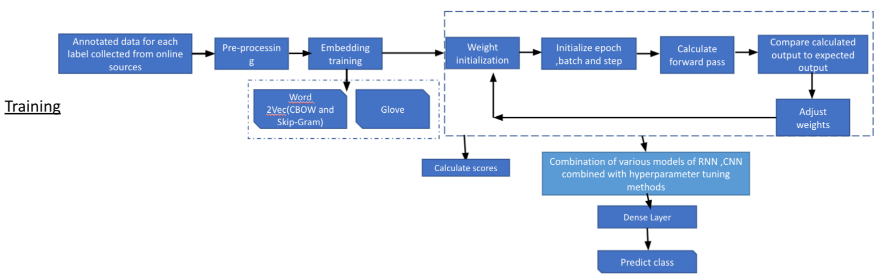
1.5 Deep Analysis - Classic NLP Pipeline

We have used the feature engineering based on the Bag of words , TF-IDF for similarity and word embeddings for similarity and context capture. The model base is then cross checked and evaluated to predict class of suicide, depressed , anxious and stressed.
The model is fitted and applied to explore the prediction class.



1.6 Deep Analysis - Deep learning pipeline

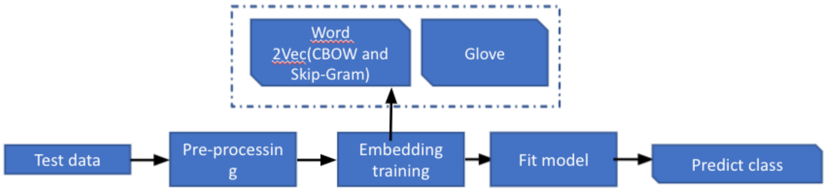
Here we have self-collected dataset via twint and manually annotated. The pre-processing methods are standard as mention in data pre-processing . Word embedding and vectorization with Glove . Weights were adjusted to reach optimal accuracy higher than 93%. The combination of the models was then fed into the Dense layer to predict the class.



1.7 Testing

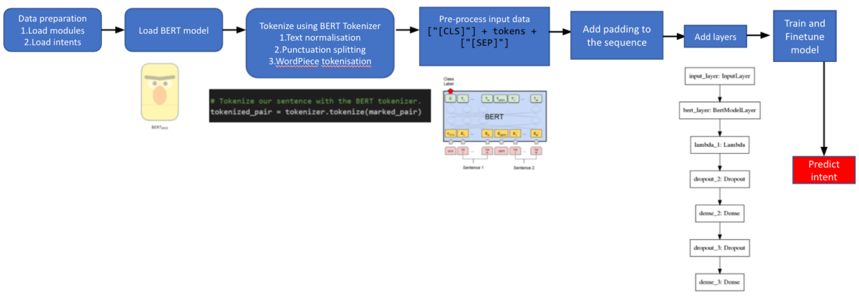
The dataset was 1/4th of the dataset was used for testing . The testing model is show as below.

Testing



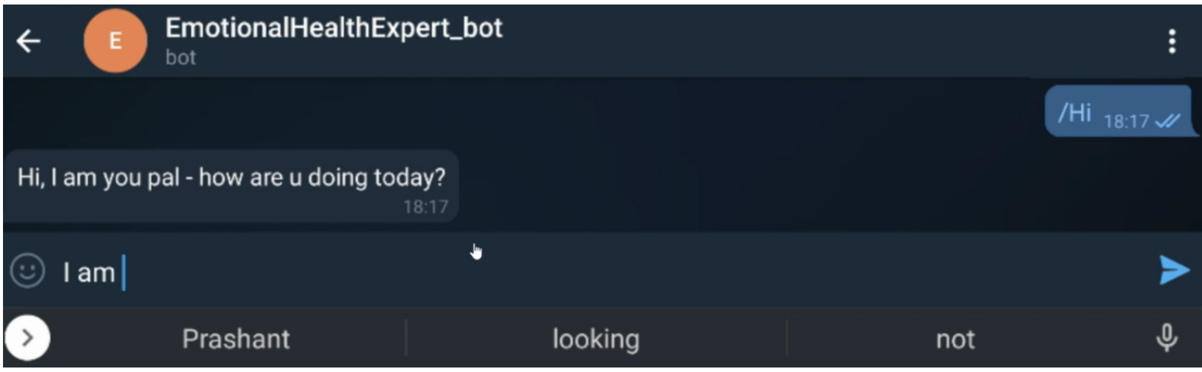
1.8 Simple Intent design

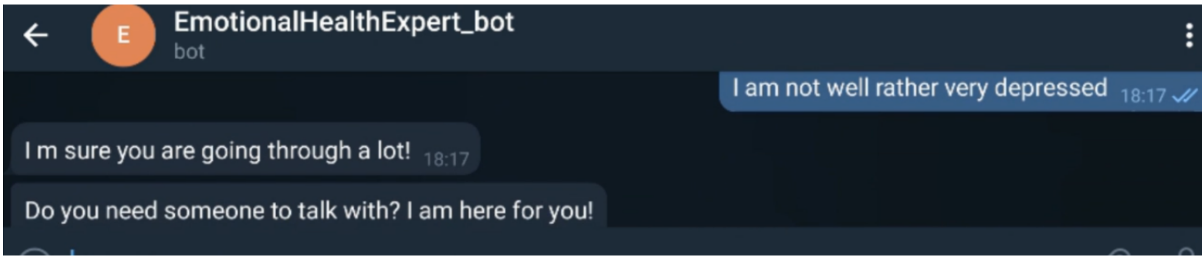
The simple intent was designed to address a generally hi, hello and greetings kind of interaction with the user. This used the intent identification trained on our dataset using BERT . The details of this model is shown in the model section 7.
Standard padding and SEP and CLS were used .
Keras and tensorflow was used for this pipeline.



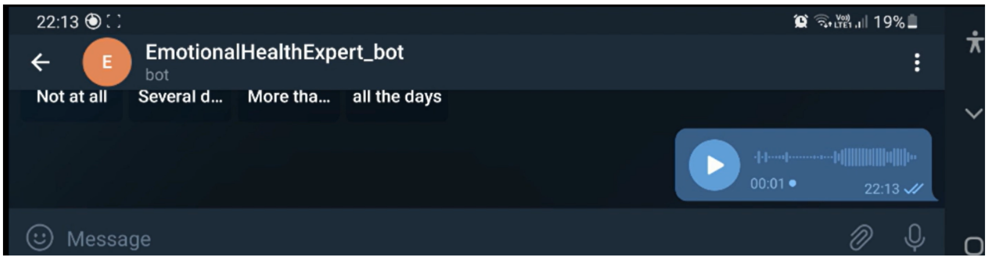
1.9 Conversation design

1. Simple Intent (Greeting): Where the user says, hi , Hello etc and is the beginning of chat.





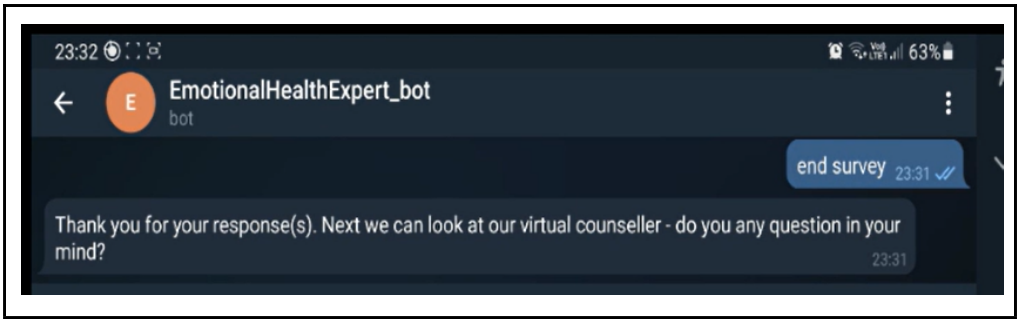
6. <u>Survey Intent</u> (Questionnaire): Here the user wants to proceed with info on a topic like depression so the chatbot gives a set of questionnaires to know more about the user situation.
   It can process both raw **text** and **audio** inputs



<u>Audio</u>

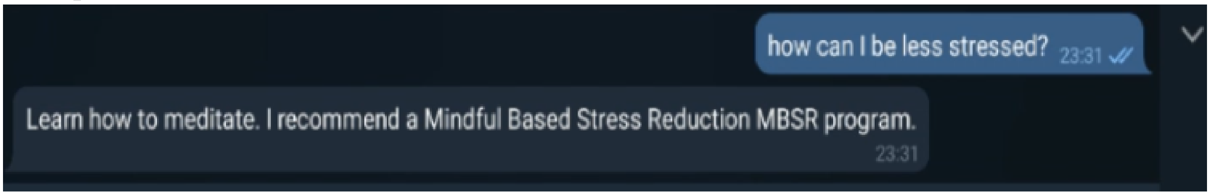
<u>Text</u>

Partial utterances are also accepted by the model as long as they are near to the intended options

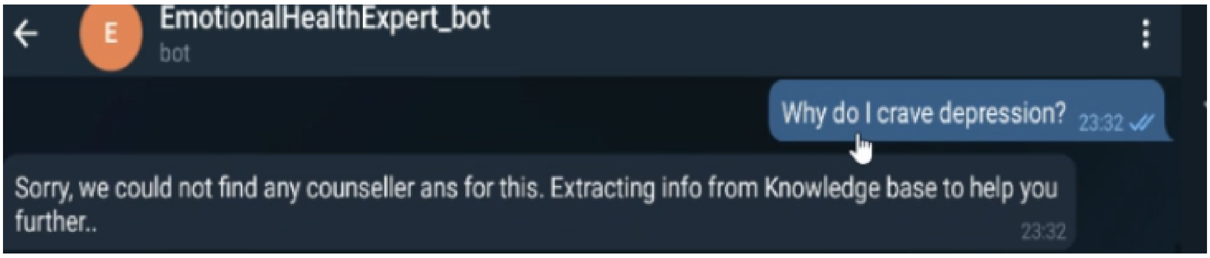


End Survey: can be used to end the survey prematurely and move ahead to Q/A intents or goodbye intents

7. Counsel Intent (Q/A Part 1): The intent where user needs help on a specific counsel question and hence chatbot triggers itself.
   Example Conversation



Response - Used cosine similarity to answer from preset ans like above
Fallback intent To use BERT Q/A



Strategy: For a given query, find the FAQ question that is closest in meaning to the user query and display it to the user. For this, we need to have an efficient way of computing **semantic similarity** between two sentences.
To compute semantic similarity between sentences, we will convert each sentence into a vector. We can then use cosine similarity between vectors to come up with a distance measure between sentences that indicates how similar they are in meaning.
The purpose of this exercise is to answer user queries by automatically retrieving the closest question and answer from predefined FAQs when appropriate
We apply data preprocessing to both the FAQ questions and the user query sentence.
Note that we have an option to not perform stop word removal. This is because some of the later models such as BERT work well without stop word removal.

Trained counsel intent as shown below.

```
text: I am suicidal
intent: counsel
Ok we will now redirect you to our virtual counsello:

text: Good morning
intent: greetings
Hi There! Let's chat. We can help you.

text: Hello
intent: greetings
Hi There! Let's chat. We can help you.
```

8. Knowledge Intent (Q/A Part 2): The intent where the user needs help on a broader question and hence the chatbot triggers itself into a document knowledge base to extract the answer. This also summarizes long answers and provides useful documents to the user for help
   Example conversation
   Fallback – simple cant say

Model and Tokenizer Initialization This is our very first step, here we will import transformers and initialize our model and tokenizer using deepset/bert-base-cased-squad2.
This is the only code we need to load in our model and tokenizer.
Input Data Tokenization We've initialized our tokenizer, and now it's time to feed it some text to convert into Bert-readable token IDs.Our Bert tokenizer is in-charge of converting human-readable text into Bert-friendly data, called token IDs.
First, the tokenizer takes a string and splits it into tokens.

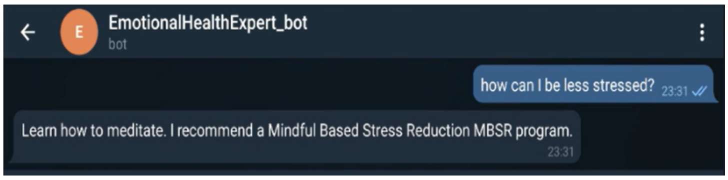
The flow as show below in multiple screenshots

```
bert_kb[0]="Sometimes it is scarier to journey into the unknown (in this case, happiness),
than it is to stay in the known, and the oftentimes comfortable space of your depression.
Human beings, for the most part, fear and stray away from change in general, especially a change that is so impactful--It isn’t abnormal.
 Anything that you are well-acquainted with can become comfortable, and that includes suffering.
 When you have been depressed for a long time, that can feel like the only natural state, so you miss it when it is gone,
 even if you know that it isn’t good for you.Indeed, depression can have a significant impact on both your health and your well-being
 PTSD can be diagnosed by your primary care provider or a mental health professional.Post-traumatic stress disorder (PTSD)is a trauma and stressor-related disorder
 that can develop after a traumatic or stressful event.Bipolar affective disorder typically consists of both manic and depressive episodes separated by periods of
 normal mood Manic episodes involve elevated mood and increased energy resulting in over-activity, pressure of speech and decreased need for sleep
 .--Self-harm is also commonly known as self-injurious behaviour (SIB),self-mutilation, non-suicidal,self-injury (NSSI), parasuicide,deliberate self-harm (DSH),
 self- abuse, and self-inflicted violence (Klonsky, 2011).As one would expect, having multiple terms for self-harm creates misunderstandingand confusion both
 in academic research and in clinical settings.COGNITIVE BEHAVIOUR THERAPY (CBT)is a psychological therapy that aims to address issues such as anxiety and depression,
 as well as a range of other mental health concerns. It helps someone become aware of inaccurate or negative thinking,so challenging situations can be seen more clearly
 and responded to more effectively.PROBLEM SOLVING THERAPY (PST)is a brief psychological intervention that focuses on identifying the specific problems that an individual
 is facing and generating alternative solutions to these problems.
Individuals learn to clearly define a problem that they face,
brainstorm multiple solutions, and decide on the best course of action"
```

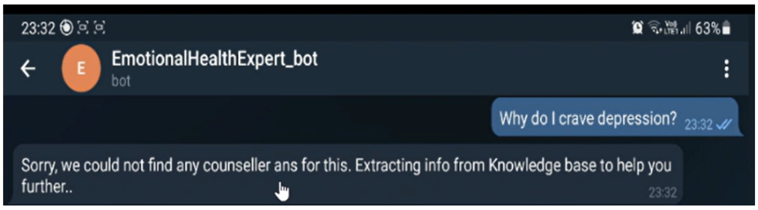
Question:We get questions from user in real time and then send it to our BERT Q/A logic.

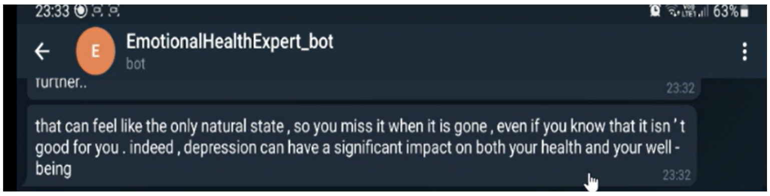
```
def q_a_bert(msg, update: Update, context: CallbackContext):
    ans = bert_question_copy.question_answer(msg, bert_kb[0])
    context.bot.send_message(chat_id=update.message.chat_id, text=ans)
```

Normal Counsel QA

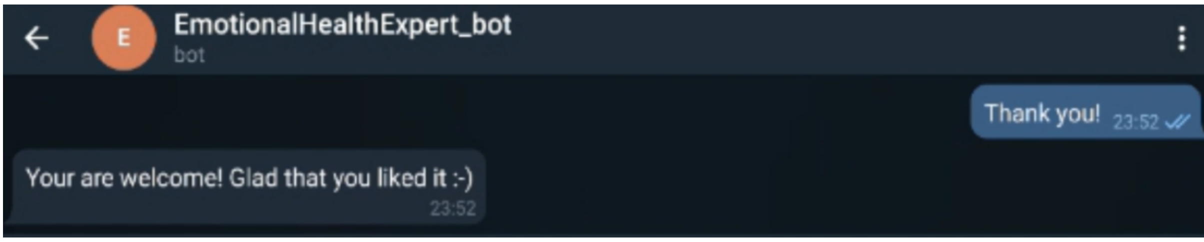


Advanced QA:

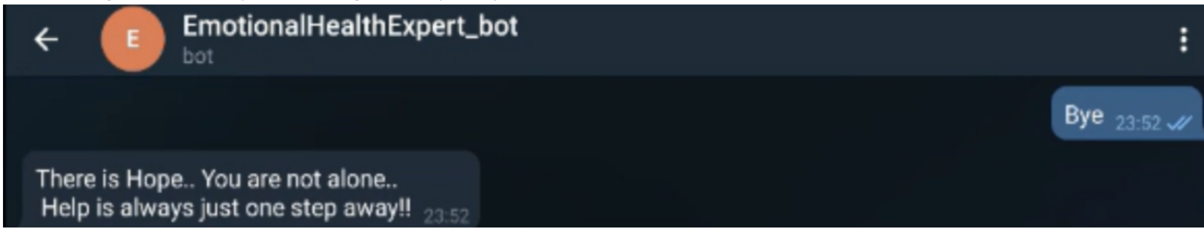




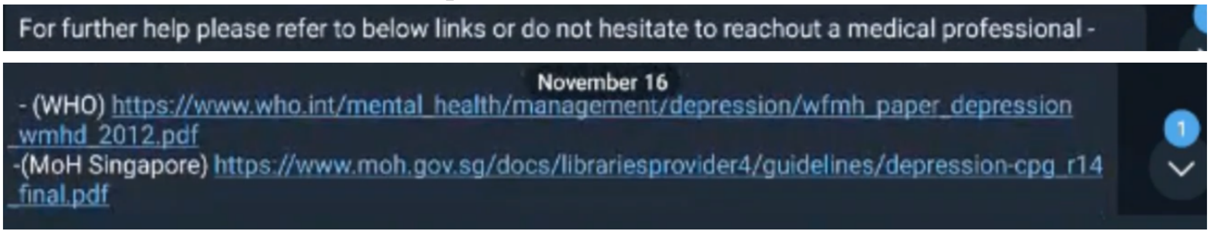
9. Ending Intent (Goodbye): Where the user says, bye, end or does not respond for a while etc and is the end of chat.



Handling of thank you and good bye bye

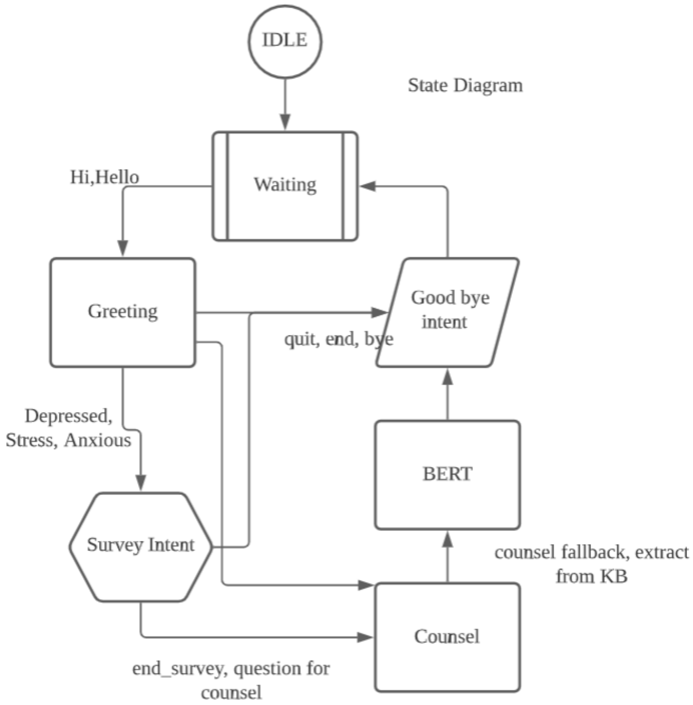


Reference material and help links



10. Response generation - we have used simple and template based response generation strategy mapped against each intent/dialog state. More than one answer is added with randomization to add variations in the chat bot replies.

1.10 Dialogue state management



- ○

1.11 Multimodal Input handling

- Text vs Audio inputs: The chatbot also captures both text and Audio inputs.
  - ○
- Browser based vs Mobile based: The Chatbot interface uses both browser based and chatbot mode and hence we selected telegram for the same.

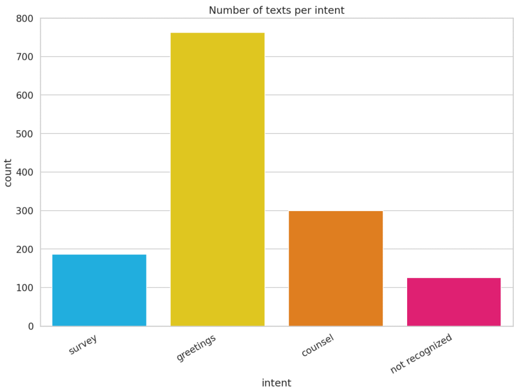
<u>ASR</u>

```
def voice_to_text(update: Update, context: CallbackContext):
    print("Say")
    r = sr.Recognizer()
    with sr.Microphone() as source:
        print("Say something!")
        audio = r.listen(source)
    with open("microphone-results.wav", "wb") as f:
        f.write(audio.get_wav_data())
    user_audio_file = sr.AudioFile("microphone-results.wav")
    with user_audio_file as source:
        user_audio = r.record(source)
        text = r.recognize_google(user_audio, language='en-US',show_all=True)
```

2 Modelling

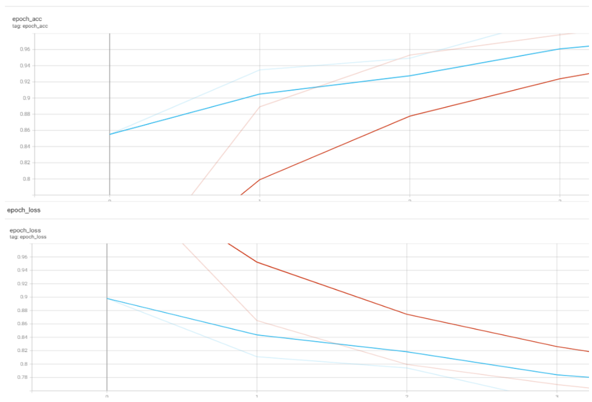
2.1 Data augmentation and analysis

The dataset was augmented by us manually using paraphrasing and back translation to increase the counsel and survey and not recognized classes. The final dataset was as below.



2.2 Training Accuracy and loss

The training involved around 5 epochs due to and the accuracy was higher than 94% after consistent efforts. The loss over training epochs reduced and the screenshot can be find below.



2.2.1 Classic NLP accuracy:

The performance metrics for our TAP accuracy can be seen as below.

b) Naïve bayes :

```
[ ]  y_pred = nb.predict(x_test)

     print('accuracy %s' % accuracy_score(y_pred, y_test))
     print(classification_report(y_test, y_pred, digits=5))
```

```
     accuracy 0.8546895640686922
                   precision    recall  f1-score   support

               0     0.84224   1.00000   0.91436      2349
               1     1.00000   0.35199   0.52070       679

        accuracy                         0.85469      3028
       macro avg     0.92112   0.67599   0.71753      3028
    weighted avg     0.87761   0.85469   0.82609      3028
```

c) Logistic regression:

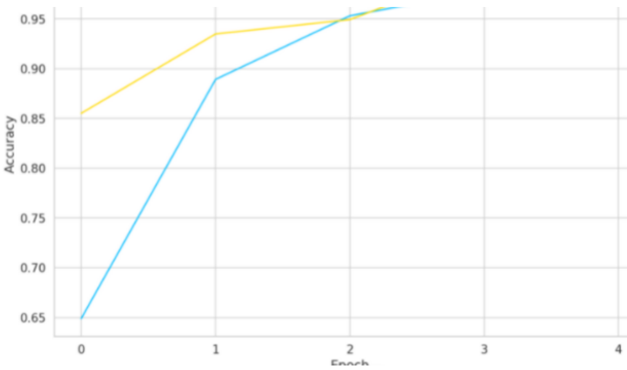
```
accuracy 0.9240422721268163
              precision    recall  f1-score   support

           0    0.96984   0.93103   0.95004      2349
           1    0.79043   0.89985   0.84160       679

    accuracy                        0.92404      3028
   macro avg    0.88014   0.91544   0.89582      3028
weighted avg    0.92961   0.92404   0.92573      3028
```

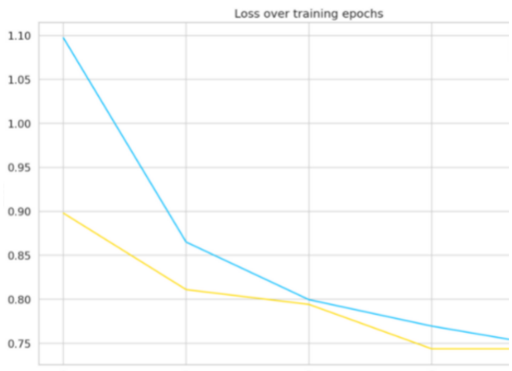
2.2.2 Intent Accuracy values

The given screenshots give the precision score for the classification report with recall and f1-score.

```
                precision    recall  f1-score   support

          survey       0.93      1.00      0.97        69
       greetings       0.96      1.00      0.98       254
             ack       0.00      0.00      0.00        14
  not recognized       0.91      1.00      0.95        42
         counsel       0.98      1.00      0.99       120
             End       0.00      0.00      0.00         8

        accuracy                           0.96       507
       macro avg       0.63      0.67      0.65       507
    weighted avg       0.92      0.96      0.94       507
```

```
Model: "model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_ids (InputLayer)       [(None, 21)]              0
_________________________________________________________________
bert (BertModelLayer)        (None, 21, 768)           108890112
_________________________________________________________________
lambda (Lambda)              (None, 768)               0
_________________________________________________________________
dropout (Dropout)            (None, 768)               0
_________________________________________________________________
dense (Dense)                (None, 768)               590592
_________________________________________________________________
dropout_1 (Dropout)          (None, 768)               0
_________________________________________________________________
dense_1 (Dense)              (None, 4)                 3076
=================================================================
Total params: 109,483,780
Trainable params: 109,483,780
Non-trainable params: 0
_________________________________________________________________
```





2.3 Response Generation

We have classified the repones generation in multiple levels. The weightage is higher on the left side. Extreme and Severe states are of Depression and anxiety and stress have high weightage in the document.

Our classification method.

- Index – the document
- Vectorize – text data
- Retrieve - its most similar documents + distance
- Find - numerical representation of text queries / chats
- Measure - similarity b/w query vector & docs

Retrieve - its most similar documents + distance

Relevance	Topic	Document
85%	Stress	Document1,Document2
50%	Lonely	Document1,Document3
30%	Depressed	Document1,Document4
22%	Anxiety	Document1,Document5

Information Extraction Task for Question answering

Pre-processing of the Docs: After the above shortlisting of the document, the text is extracted from PDF resources, pre-processed, segmentation is performed and then it is converted to a simple text representation suitable for BERT question answer to process as an input context. Various knowledge base buckets are created for different labels percentages like Depression + stress, Stress & Anxiety, or Loneliness alone etc.

BERT Q/A: When a user triggers a question that is not handled by counsel intent then BERT Q/A is invoked on the relevant context and the answer is responded back to the user.
It is completely handled by BERT.

Postprocessing of the answer involves summarization if the answer is longer than a couple of sentences. In case of no answer and standard text is returned with apologies.

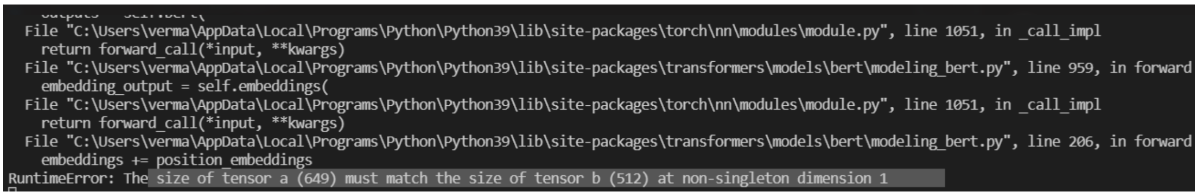
2.4 Results and Analysis:

We evaluated our method on the Twitter & Reddit datasets. The experimental results showed that the proposed emotion-based network model achieved an accuracy, precision, recall, and F-measure of 91.30%, 91.91%, 96.15%, and 93.98%, respectively, which are comparable results compared with state-of-the-art methods.
Thus it assists users to help with self-improvement.
Future enhancement can be done here to engage with healthcare professionals based on user engagement.

2.5 Challenges

- A lot of junk tweets and posts to filter out.

- Cases like Sarcasm was difficult to be analysed
- Dialogue state and Response generation for out of context utterances was tricky to handle.
- Multimedia Tweets are ignored because the focus is on text.
- Difficult to scrape without using depression-related keywords.
- The class imbalance between actually depressed tweets and suggestive help material.
- Difficult to classify between various emotions under the depression quadrant and lack of training dataset.
- Slowness observed in BERT due to lack of computational power.
- Another challenge was tensor size had to be regulated by us to not exceed 512.



```
  File "C:\Users\verma\AppData\Local\Programs\Python\Python39\lib\site-packages\torch\nn\modules\module.py", line 1051, in _call_impl
    return forward_call(*input, **kwargs)
  File "C:\Users\verma\AppData\Local\Programs\Python\Python39\lib\site-packages\transformers\models\bert\modeling_bert.py", line 959, in forward
    embedding_output = self.embeddings(
  File "C:\Users\verma\AppData\Local\Programs\Python\Python39\lib\site-packages\torch\nn\modules\module.py", line 1051, in _call_impl
    return forward_call(*input, **kwargs)
  File "C:\Users\verma\AppData\Local\Programs\Python\Python39\lib\site-packages\transformers\models\bert\modeling_bert.py", line 206, in forward
    embeddings += position_embeddings
RuntimeError: The size of tensor a (649) must match the size of tensor b (512) at non-singleton dimension 1
```

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