Deep Learning-based Solution for Mental Health Issues

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The current paper proposes a solution for the nowadays mental health problems using artificial intelligence algorithms. Making use of natural language processing (NLP) techniques, the main idea is to construct a conversational agent which can act as a psychologist. This can be possible by implementing sentiment analysis on the patient's input text. In order to cope with the user's feelings, the chatbot is developed to perform cognitive behavioral therapy (CBT) exercises with him or her. These exercises are effective even in an online environment. The analysis performed by the sentiment model will detect a dominant emotion in the user's behavior and in this way the bot will adapt the conversation for obtaining better results.

Keywords: *Deep Learning, Natural Language Processing, Chatbot, Artificial Intelligence, Cognitive Behavioral Therapy*

1 Introduction

During the last years, the artificial intelligence (on short, AI) field has become more and more popular, being used in a vast number of newly developed software applications. Besides other examples, chatbots are one of the most frequent tools used in today's solutions.

There are multiple reasons behind the increased number of conversational agents used in software products now. Depending on the application's domain, the reasons can vary from increased efficiency among support teams up to better understanding of the customer's needs and behaviour while using the software. By simulating human-like conversations, the users find these conversational agents very practical when it comes to requesting help, needing online guidance or just some advice regarding a specific topic.

Recently, AI chatbots started to be present in many applications used in the healthcare field. From offering real time diagnosis to conducting small online appointments, they ease the access to medical help in many cases.

In a study conducted in 2018, it was concluded that despite the improvements and evolutions of the technology, there is a significant number of internet users who do not trust online healthcare tools, mainly chatbots, for several reasons such as the lack of trust in the prediction of the diagnosis or in technology in general [1]. However, when it comes to mental health advise, people seem to be open to use these online tools. After having a conversation with an AI chatbot, many individuals declared that their level of stress decreased [2]. More than that, persons with severe symptoms of depression registered better results in the improvement process while using a chatbot designed for mental health issues compared to those obtained after a clinical session [3].

In this paper, I aim to create a rule-based chatbot which will be trained according to Cognitive Behavioural Therapy (CBT) techniques for helping its users to cope with different predominant emotions encountered in their daily life. The chatbot will be integrated in a web application so that it can be accessible whenever and wherever the user feels the need, as long as they have access to a device with internet connection.

I strongly believe that mental health status affects the daily activity of an individual regardless his age or profession. The most recent global event, the COVID-19 pandemic, had a negative impact on our mental health. Alongside the panic caused by the new virus, the lockdowns and the

imposed restrictions prevented the contamination, but caused other problems such as unemployment, change of daily routines, adaptation to new (in the case of virtual meetings related to work and school) which are well-known triggers for anxiety and depression for an individual.

According to an article published in the National Library of Medicine [4], the social distancing measure caused social anxiety, emotional disturbance, insomnia or even depression in some extreme cases. The same article states that there is enough evidence to sustain that the infection with the virus can cause some severe mental health issues. In the acute stages, infected individuals presented delirium. After the recovery, there is still some data which shows that depression or anxiety are present up to 1 year after infection.

In term of numbers, National Alliance of Mental Illness conducted a study [5] in United States which shown that 1 in 6 teenagers (aged 12-17) experienced massive depression episodes in 2020 and over 3 million of them had serious thought of suicide. Moreover, there was an increase of 31% in the number of emergency mental health department visits for patients at this age. In addition, 23% of young adults (18-25 years old) admitted that the pandemic had a negative significant impact over their mental health status.

These alarming numbers strengthen the idea that mental health should be carefully analyse at all ages. Giving the fact that sometimes children and adults do not have access to supervised help in the domain of psychiatry, AI conversational agents could improve their mood and act as a treatment for their issue.

2 Cognitive behavioral therapy

Cognitive behavioural therapy (CBT) is a psychological therapy technique which based on talk, has as aim the management of the patient's problems by changing his problematic thoughts and behaviour. It was developed in the United States during the second part of the 20th century.

According to this technique, the problematic thoughts are broken into small parts and for each of them it should be found a positive coping aspect. The hole process is based on the current issues encountered by the patient so that the actual negative feelings would change quickly and stop affecting his life.

The advantage of the CBT therapy is that its specific techniques that are implemented can vary from one therapy session to another, guided by a psychologist or self-help exercises done individually. Within the recovery process, the patient will be encouraged to use diverse tools such as journaling, relaxation techniques or even role-playing. In addition to the wide range of coping mechanism, the strategies based on cognitive behavioural therapy rules are effective both during in-person training session and also in online solutions such as monitoring applications or virtual meetings with a mental coach. [6]

However, the CBT strategy does not have as final objective to label the patient's issues and make him aware of his disease. This therapy is built over the idea that it is more efficient to find strong and healthy arguments which can improve his behaviour. The key words of CBT are identifying negative thoughts, practicing new skills and goal setting.

Cognitive behavioural therapy can help with a large set of frequent mental health issues which are affecting people nowadays. These are:

-        Anxiety
-        Depression
-        Eating disorder (bulimia)
-        Phobias
-        Bipolar disorders

However, cognitive behavioural based exercises can also solve a range of common problems which cause discomfort among individuals such as:

-        Grief and loss
-        Low self-esteem

- Stress management
- Relationship problems
- Addiction issues (drug, alcohol)

The patient who is involved in any kind of cognitive behavioural therapy should have a significant level of motivation for changing his mental-damaging thoughts and actions. The entire process may consume a lot of energy because the problematic thoughts should be carefully analysed. The alternative thoughts that are aimed to combat the problem need to be constructed around a neutral idea which will not generate any other harm to the mental health.

The current AI driven chatbot presented in this paper will focus on treating users' issues applying a CBT technique called cognitive restructuring.

Cognitive restructuring [7] is focused on the identification of harmful behaviours and thoughts followed by building a correction mechanism against them. This mechanism consists of a set of alternative thoughts that will trigger fewer negative emotions to an individual's mind.

The cognitive restructuring should not be associated with a positive thinking manner [8]. In this case, the focus is not on a drastically emotional change. For example, the objective is not to make an anxious patient instantly happy. He needs to understand the reasons for his anxiety, find some alternative actions which can help in lowering the emotion intensity and apply them every time he encounters himself in a similar situation.

By applying constantly cognitive restructuring exercises over a predominant problem, the patient will notice a more relaxed, happy mood. Also, he will experience a newly developed way of thinking and behaving. The situations which usually caused him negative emotions now will be overpass without any significant damage on the mental state.

A very common way used for solving negative thinking using cognitive restructuring is called thoughts recording.

In the application described in my thesis, the chatbot will apply this exercise with every user which presents signs of depression, anxiety or anger issues.

The steps of completing this exercise are the following ones [8]:

a) Identifying the problematic thought or action

This step is represented by the clear identification of the thought or idea that generated the negative emotion felt by the patient. For reference, this idea will be called automatic thought, as it is the first impulse that the patient's mind reveals when facing a certain event.

b) Constructing different points of view over the identified damaging pattern using a set of predefined questions

During this phase, the patient should answer to different questions which will make him have a better understanding over the essence of his problem.

Questions like "what is the effect of believing this thought?", "what would happen if you stopped believing this idea?", "what is the rational evidence of keep trusting this thought?" will make the patient aware of his present thoughts. In this way, he will observe them from an objective perspective. This is the starting point of changing his focus from being overwhelmed by the amount of negative emotions experienced to the process of solving the current issue.

To dive deeper into the problem, asking the patient to find an alternative explanation for his automatic thought could force him to take into account other variables that were not considered before. As an example, he may find out that overthinking some actions may trigger a high level of anxiety in his mind. The entire process generated in the patient's mind while he is trying to respond to this particular question will open multiple doors for new possibilities which can solve the main problem.

The final point of this step is to identify the worst-case scenarios that can be caused by

the automatic thought. Going through this phase, the patient starts to have a clearer picture over the situation built in his mind. In case of anxiety or depression, this could be the key moment when the level of negative emotions starts to decrease as the patient realises which parts of his imagined scenario are probably to happen and which are just augmentation of a fake reality.

c)   Imagining a scenario in which you would give advice to a friend which is confronting with a problem similar to the previously identified automatic thought

The depersonalisation process involved in this step has many benefits on the patient way of thinking. Here, it is implemented using a well-known psychological strategy called role-play.

After analysing the patient's thought, we can observe that he is stuck in a vicious circle formed by his own harmful thoughts. This may isolate him from seeing the bigger picture and thus everything will look and feel worse than it actually is.

By transposing the same problem to an external person (in this case, a close friend), the patient will escape from the infinite loop created in his mind and will try to find the best arguments to make his friend feel better. As soon as the encouraging words are found, the patient will observe that his similar problem has a solution, so the intensity of the negative emotions will drop.

The long-term benefit of this type of mental exercise is that it will increase the empathy and the self-esteem of the patient, so emotions like anxiety, depression or fear will affect less his overall well-being.

d)   Constructing the final alternative response which will combat the automatic thought

The last step of the thought recording exercise is to build the final alternative response. The alternative response is the concept that will help the patient to cope with the automatic idea that caused his entire set of overwhelming emotions.

Analysing the answers formulated at the previous steps, the patient may try to find an alternative response, suitable for diminishing the source of the problem. It can be used to calm his emotions every time he will find himself in a similar situation.

As a conclusion regarding the effectiveness of the cognitive restructuring, a study published in August 2014 in "Journal of Anxiety Disorders" showed that this technique significantly decreased the possibility of developing post-event processing (PEP) thoughts. The concept of PEP thoughts refers to the reflective ideas that an individual can experience after a social event. Usually, those thoughts are automatic and cause anxiety as they focus on possible bad or embarrassing actions done while interacting with others. [9] [10]

3 Application architecture and data flow

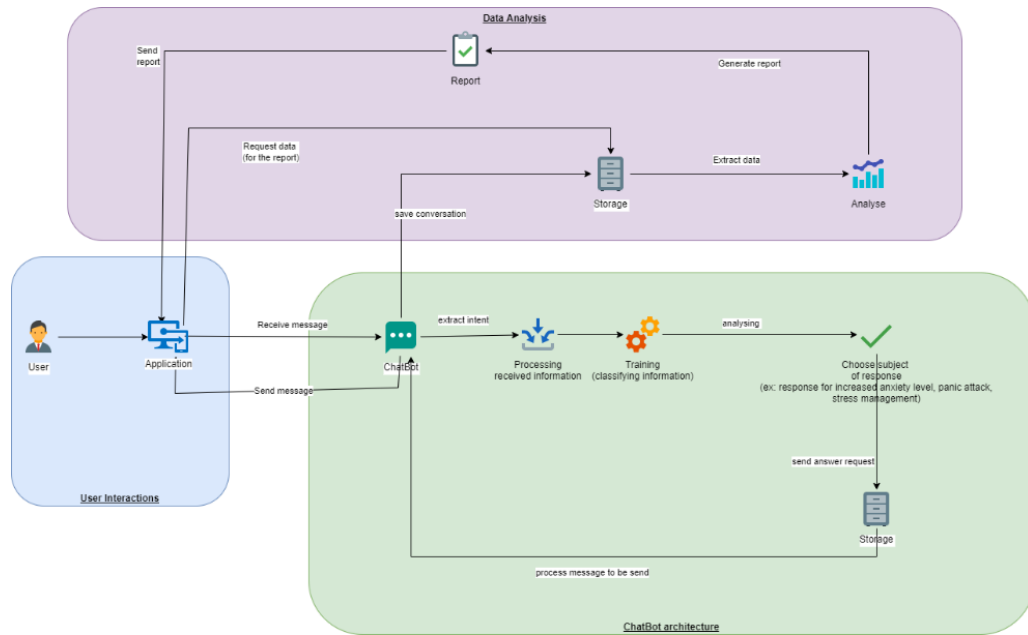Regarding the application architecture, it is presented in the figure below:

Fig. 1. Application architecture

As it can be noticed, the application consists of three levels:
- User interface
- Chatbot architecture
- Data analysis

a) User interface

The user interface part represents the initial interaction between the user and the application. The user must be connected to the web application in which the chatbot is integrated.

The backend of the web application is built using Flask, a web framework which gives the possibility to create such application based on one or many Python files. However, for adding multiple functionalities to the application, the Flask project can also contain HTML, CSS or JavaScript files. [11]

For styling the application, I used HTML (Hyper Text Markup Language) and CSS (Cascade Style Sheets). The web pages and also the chat box are constructed using these tools for making the experience more appealing to the user. The design is based on the idea of a sky full of clouds. This image is usually relaxing, so the user's feelings may be influenced by this concept.

Moreover, there is a JavaScript attached to the Flask project for handling the events of the chat box. In general, this programming language is used for managing special effects of a web page.

An important aspect to mention here is that the developed web application is a responsive one, so it can be used on multiple type of devices (computer, phones or tablets) as long as they have a stable internet connection.

b) Chatbot architecture

Once the user launches the chat box from the web application, the conversation with the chatbot starts. The chatbot architecture is one of the most complex parts of the application. It has multiple components:
- Processing user messages
- Analysing user messages and identifying the predominant sentiment
- Processing bot replies depending on the identified scenario

Initially, the bot will present itself explaining what its purpose is and what therapeutical techniques is it using. After that, it will involve the user into the conversation by asking what his name is. An important but simple question is addressed afterwards. The bot will ask the user to

describe what are his current life issues. This step has as objective the identification of the sentiments felt by the user. In this step, it will be involved the sentiment analysis model detailed in the Sentiment analysis paragraph.

From here, the bot can adapt to two main scenarios depending on the type of emotion. If the emotion is a positive one, the bot will guide the user throughout a journaling exercise and it will encourage him to talk about his day or detail his current feelings. In addition, the bot can make podcasts suggestion based on the user's preferences.

In the other scenario, when negative emotions are present in the user's description, the bot will start using the cognitive restructuring techniques with the help of the exercise called thought recording. During the exercise, the bot will try to extract the source of the user's emotional problems. Firstly, the problematic thought will be identified with the help of the user. After that, the bot will put a set of predefined questions which will offer a clearer picture of the problem. Once all the questions are answered, the user will need to choose an alternative thought that will help him to overcome the situation induced by the initial automatic thought.

The alternative thought developed by the user will be also analysed by the sentiment model. On one hand, if the predicted emotion of the alternative response is a negative one or if there is no significant improvement between the final and the initial thoughts, then the bot will suggest the user to seek for professional help. For this, the user can contact one of the psychologists who are listed in special section of the web application.

On the other hand, if there is a major improvement in the way in which the user thinks, then the bot will congratulate him and finally the conversation will end. The entire conversational process is done using multiple Python functions. The bot

replies are extracted from files as dataframes using the *pandas* package. The methods which are used for building the sentiment model are detailed in the next section.

Each conversation is saved in a JSON file which will be used for generating the report detailed in the next step. Initially, the user responses are stored progressively into a Python dictionary and in the end, it is converted into a JSON file using the *dump* method from the *json* package.

c) Data analysis

The last component of the application architectural scheme is the data analysis part where the final report will be generated.

The previously saved JSON file containing the messages between the user and the bot will be analysed using different data analysis technique. In this way, a report will be generated as a line chart graph. It will highlight the emotional process in which the user was involved during the conversation with the chatbot. This is an important tool if the user would like to take evidence of his mental health status during a certain period of time.

For completing this step, I used different Python packages such as *pandas, pyplot, matplotlib* and *json*.

4 Sentiment analysis

Text mining is the process of developing meaningful insights from unstructured pieces of text. Originally, it was a part of the Natural Language Processing (NLP) technique which is a subcategory of the Artificial Intelligence (AI) field.

Natural Language Processing (NLP) contributes to the communication between machines and humans. With the help of some specific algorithms, it makes a computer understand and process the human language. Examples of fields in which NLP is used are spell check systems, online translation solutions and so on.

Sentiment analysis is one of the many Natural Language Processing (NLP) applications. It has as objective the extraction of the emotional component

behind a portion of text. This analysis requires the use of Machine Learning (ML), Artificial Intelligence (AI) and text mining techniques in order to implement it properly.

Nowadays, sentiment analysis algorithms are most frequently used in organizations that interact directly with clients. These algorithms help the enterprises to have an overall image of the customer's feedback regarding their services or products. Depending on the performed analysis, the decisional team may develop new strategies for improving the clients' experience.

a) Implementation

There are several types of sentiment analysis, but in this paper, I will focus on the one in which there will be extracted four categories of emotions out of a text: sadness, fear, anger and joy.

The analysis will be implemented in Python. In general, Python is used for applications developed using machine learning, artificial intelligence, or natural language processing methods because it provides numerous libraries that help with the mathematical computations encountered in the implementation of these fields.

The training dataset consists of a series of tweets placed into a text file. The structure of the file is the following: the number of the tweet in the text file, the corpus of the tweet (including tags, emojis and hashtags), the emotion expressed by the tweet and a threshold which shows the intensity of the expressed sentiment.

Using the *pandas* package, the data is stored into dataframes depending on the expressed sentiment. The distribution of the emotions was draw using the *pyplot* module from the Matplotlib package. It represents how the tweets are distributes over the entire dataset.
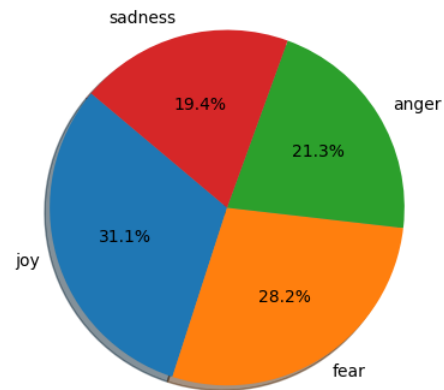

Fig. 2. Distribution of sentiments in the training dataset

As the pie plot suggests, the sentiments seem to be almost equally distributed in the training dataset. However, the number of tweets which express joy is the largest while the tweets that express sadness are the fewest.

An important part of the sentiment analysis could be to highlight the most frequently used words in the training dataset to express each emotion. For this, I used the WordCloud package which helps with this overview of the most recurrent words. This package is generally used for data visualization. It gives as output an image with the most frequent words of a text. The higher the font of the word, the higher the number of occurrences in the analysed text.

Fig. 3. Most common words used to describe sadness

In the training dataset it seems that words like "sadness", "lost", "depression", "sober", "unhappy", "sad", "discouraged" or "dark" are often used to express sad thoughts. There was a high probability that these words will be pressed in the data set containing sad tweet messages. However, there are some

words which are not normally expected from a sad lexical field, namely "time", "day", "know" or "will". An explanation for this may be the fact that these words are among the most frequently used words on Twitter [12].

On the other hand, in the data set collecting the fear thoughts are repeatedly found words like "fear", "nightmare", "afraid", "bully", "terrorism", "shocking", "afraid" or "anxiety". Generally, those are the words which form the lexical field of fear.

When it comes to expressing their anger, most people used in their tweets words such as "angry", "anger", "bitter", "people", "offended", "revenge", "furious" or "insult".

The most common used word to describe joy in the data set which represents the tweets expressing thoughts of joy are "happy", "smile", "love", "amazing", "delight" and "laughter".

Usually, data visualization procedures contribute to a better understanding of the analysis that follows to be done.

The sentiment analysis algorithm that I have developed is composed of three parts:
- Normalization of the text
- Vectorization of the text
- Building the sentiment model

b) Normalization

The process of normalization means extracting the most relevant information out of a text after it is cleaned, tokenized and stemmed. In the text cleaning part, all the emojis, user tags, hashtags, URL links and abbreviations should be removed from the tweets. In this way, only the main parts of each sentence will be kept.

The tokenization method consists of splitting the pieces of text into smaller groups of words. There are several ways in which this algorithm can implemented. In this paper, I chose to define a custom function in which I provide the options to eliminate the numbers, the punctuation

signs and the stop words from the text. The notion of "stop words" refers to the pronouns, articles, prepositions or conjunctions normally presented in a text. They would not contribute to the sentiment analysis, so this is the reason why they should be eliminated before performing the analysis

The main package that I will used to perform this task is the NLTK package. This package gives numerous facilities for tokenizing a text. The most important one is the module which uses the word tokenization principle, meaning that it extracts each word of the provided text. Moreover, the same package makes the extraction of the stop words easier.

```python
def custom_tokenize(text,
keep_punctuation=False,
keep_alphanumerical=False,
keep_stopwords=False):
    token_list = word_tokenize(text)

    if not keep_punctuation:
        token_list = [token for token in
token_list if token not in
string.punctuation]
    if not keep_alphanumerical:
        token_list = [token for token in
token_list if token.isalpha()]

    if not keep_stopwords:
        stop_words =
set(stopwords.words('english'))
        stop_words.discard("not")
        token_list = [token for token in
token_list if not token in stop_words]

    return token_list
```

The custom function will give the possibility to choose if the punctuation, the numbers or the stop words should be kept or not. An important aspect of this function is that it drops the word "not" from the list of stop words. By default, there will not be dropped. Considering the objective of this project, the word "not" can have a major impact on the sentiment analysis.

The stemming method refers to the process of reducing a word to its root. Being a normalization technique, it ensures that two or many derived words coming from the same root word will be processed as one (the root one) by the machine. As in the previous

text, the normalization step, one of the most useful packages is NLTK. There are several modules in this package that provide different algorithms for stemming, but the one chose for this project is Snowball stemmer which is known also as Porter2. The main reason for which I chose to use this module is that the algorithm behind it returns a better root of the word then Lancaster or Porter stemmer does.

c) Vectorization

The text vectorization method is the process in which the text is represented in a numerical format. This approach makes the text understandable by the machine. Term Frequency – Inverse Document Frequency (TF-IDF) algorithm is usually the most versatile solution for solving this issue. It offers a way of calculating how relevant is a word in a text. The relevance of the word increases proportionally to its number of occurrences in the given text.

In the term frequency (TF) part, it is computed the weight of a term based on its occurrences in the document. The term of "document" refers to a part of the text that needs to be analysed. For example, if the text on which the vectorization will be performed contains three sentences, then each sentence will be called "document". Term frequency method highlights the relevance of a specific term in the given text as the value of important terms will be higher than the others. It has the following formula:

$$tf_{w,d} = \frac{n_{w,d}}{\sum_k n_{w,d}} \quad (1)$$

where:

- w = current word to be analysed
- d = document on which the vectorization is performed
- n = number of occurrences of the word in the document

Document frequency (df) computation is similar to term frequency one, but the only difference is that in this case the focus will be on the occurrences of a term in the data set.

The next part in the algorithm is the computation of the Inverse Document Frequency (IDF). It tests the relevance of a word according to the entire text. It is computed using the formula:

$$idf_w = log_2(\frac{N}{df_w}) \quad (2)$$

where:

- w = current word
- N = number of documents
- df_w = document frequency of the word

The final step in the TF-IDF computation is the multiplication between the TF and IDF. The obtained result will suggest if the word is significant or not to the analysed text. The higher the score of the word, the higher its significance.

The next figure summarizes the computations performed during the vectorization method giving a practical example:
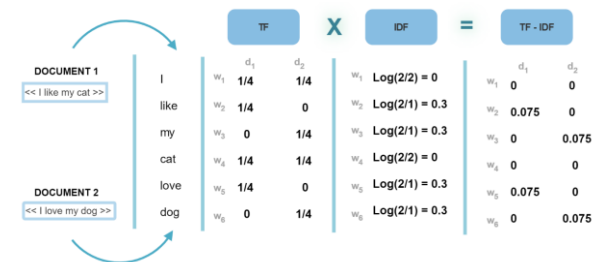

Fig. 4. Term Frequency – Inverse Document Frequency (TF – IDF) Vectorization Method

In Python, the vectorization algorithm is implemented using the TfidfVectorizer method from the *sklearn* module.

d) Building the sentiment model

A main part of building the sentiment analysis model is to split the data in two sets: training data set and testing data set. The model is represented by a multiple

linear regression which means that the independent and dependent variables should be identified. In the current built model, the independent variables will be represented by the tokenized form of each tweet which needs to be analysed while the dependent variable will be its associated sentiment. Based on this observation, 80% of the data will be allocated for training the model while the rest of it will be used for testing it.

Once the split is done, the vectorization method will be applied on both training and testing sets of the independent variables. This procedure needs to be done before building the sentiment model. It ensures that the text is transformed into numerical values and the necessary computation can be realized without any impediments.

Considering the fact that there are four sentiments to be identified in the analysed text (namely sadness, fear, anger and joy), each emotion needs to have a score based on which the prediction will be performed. The score is allocated as it follows:
- If the tweet expresses sadness, its score will be 0
- If the tweet expresses fear, its score will be 0.33
- If the tweet expresses anger, its score will be 0.67
- If the tweet expressed joy, its score will be 1

The multiple linear regression equation has the following structure:

$$estimated\_sentiment = \beta_0 + \beta_1 * x_1 + \beta_2 * x_2 + \beta_3 * x_3 + \dots + \beta_n * x_n$$

$$(3)$$

Where:
- estimated_sentiment = the predicted numerical value which will be associated to a sentiment
- β_i = the coefficient of the regression
- x_i = independent variable

Based on the scores previously allocated, the prediction will be done in the next manner:
- If the estimated_sentiment variable is lower than 0.33, then the expressed emotion is sadness
- If the estimated_sentiment variable is between 0.33 and 0.67, then the expressed emotion is fear
- If the estimated_sentiment variable is between 0.67 and 1, then the expressed emotion is anger
- If the estimated_sentiment variable is higher or equal to 1, then the expressed emotion is joy

Note that both the score allocation and the score prediction may be adjusted depending on the data set on which the model is built.

In Python, the *sklearn* package provides the Linear Regression model which helps with the construction of the regression equation.

Having all these steps put together, the function that gives an interpretation to the sentiment analysis is defined as:

```
def predict_text(text):
    processed_text =
function.process_text(text)
    transformed_text =
tf_idf.transform([processed_text])
    prediction =
final_model.predict(transformed_text)

    if prediction >= 1:
        message = "Prediction is: joy"
    else:
        if (prediction >= 0.67) and
(prediction < 1):
            message = "Prediction is:
anger"
        else:
            if (prediction >= 0.33) and
(prediction < 0.67):
                message = "Prediction
is: fear"
            else:
                if prediction < 0.33:
                    message =
"Prediction is: sadness"

    return prediction, message
```

5 Application functionalities

In the last section of this paper, I will present the available functionalities of the described application. As mentioned before,

my solution has a web application which has an integrated chatbot which makes use of cognitive behavioural therapy techniques.
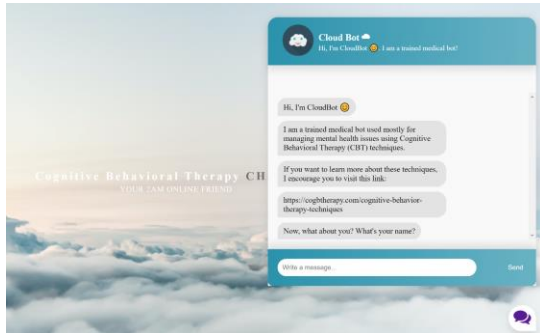

Fig.5. Initial page

In **Fig.5.** is illustrated the initial web page which is loaded at the launching of the application. There are brief descriptions of both the cognitive behavioural therapy and chatbot characteristics and purposes. Besides that, there can be found the chat box where the conversation between the user and the bot takes place. By default, the first messages of the bot are directly generated in the HTML file of the chat box. Once the user will send the message containing his name, the conversation will continue.

The bot can adapt to three main scenarios:

1. Anxiety and depression (or negative) scenario
- If the analysis performed on the user's main problem predicted that the dominant sentiment is either sadness or fear
2. Anger (or neutral) scenario
- If the model predicted anger emotions regarding the user's concern
3. Happy (or positive) scenario
- If the user may emotion predicted by the sentiment model is joy

Both negative and neutral scenarios involve the use of the thought recording exercise. In each case, it will be adapted to the specific characteristics of the dominant feeling.

In the following part of this section, I will show the steps that are implemented by

the bot if the user has issues which cause him a significant level of anxiety and depression.
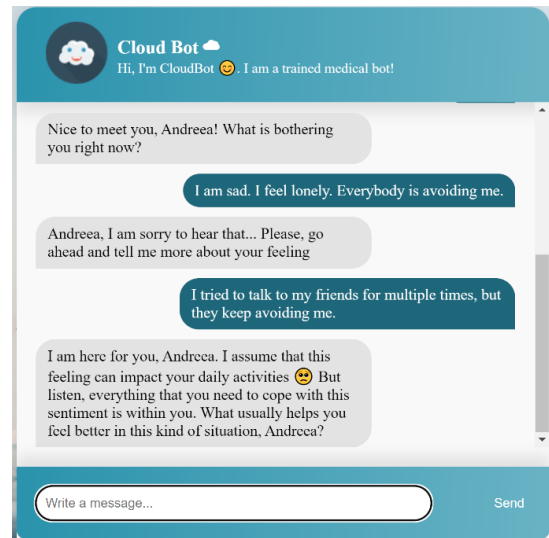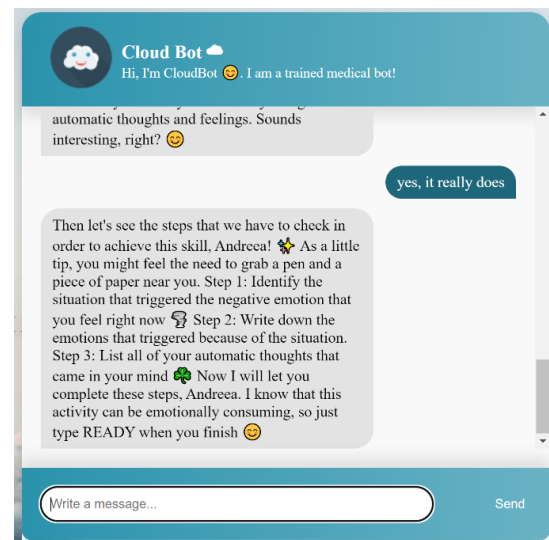

Fig.6. Conversation based on a negative emotion

Fig.7. Conversation based on a negative emotion

Fig.6. illustrates the starting point of a scenario. Once the user answers to the question regarding his actual issue, the bot will perform the sentiment analysis on his response and thus it will decide what type of scenario is suitable for the current user.

In the given example, the user reports sad feelings by explaining that he is sad and lonely. As a result, the bot initiates the thought recording exercise. Firstly, it will present the characteristics of the exercise

and the techniques that will be involved in it.

As it can be seen in **Fig.7.**, the bot exposes the necessary steps to be done for correctly performing this exercise and asks the user to express what is the automatic thought that is causing him emotional discomfort.

Moving on, the conversation will continue with a set of predefined questions put by the bot. The scope is to create an objective perspective over the problem. In this way, the user will be detached from his auto-generated feelings and would be more capable of finding a solution.

However, when the user finishes answering all the questions, the bot will ask him to build an alternative response to his initial thought which will make him feel better. In this manner, the bot will conclude if the exercise was effective or not.

The sentiment analysis will be performed on the alternative thought identified by the user. If there is a significant improvement between the initial mental state and the final one, then the user will be congratulated and the conversation will end, otherwise the bot expresses his apologies and will guide the user to consult a professional therapist.

As mentioned before, in the case of predicted angry issues in the user's behaviour, the bot will follow similar steps with the ones presented above in the explanation of the negative scenario.

However, if the bot identifies that the predominant emotion felt by the user is a positive one, it will act like a journal by encouraging him to detail his daily activities. In addition to that, the bot will make suggestions regarding online sources that would keep the user in a happy mood such as online guided meditations or therapeutical podcasts.
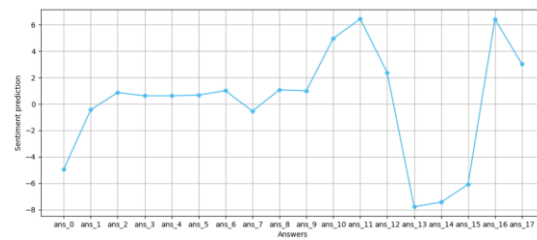

Fig.8. Graph based on the conversation when user identified an efficient alternative thought

The last functionality of the application is the final report that will allow the user (and his therapist if needed) to have a better understanding of the emotions that were involved while he was talking about his thoughts. This report is represented by a line chart which contains the sentiment prediction coefficient corresponding to each of the user's answers.

In general, the higher the coefficient, the happier the mood of the user. The graph generated based on the conversation presented above (**Fig.8.**) clearly shows that during the first messages when the user was exposing his issues, he was overwhelmed by negative emotions. As he started the thought recording exercise, his mood significantly improved. The conversation ended with a high score because the user was able to find a positive thought that could change his initial mental state.
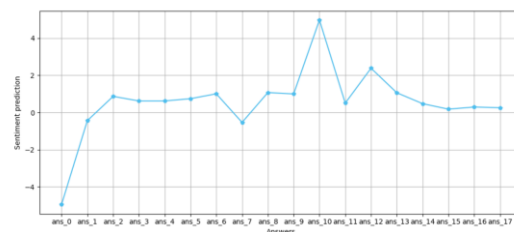

Fig.9. Graph based on the conversation when user didn't identify an efficient alternative thought

On the other hand, **Fig.9.** is the report generated when the user is not able to find an efficient alternative thought. The last answer's coefficient is almost 0, meaning that the assumed sentiment for it is a negative one.

6 Conclusions

This paper aimed to highlight the constant evolution in both technology and healthcare industry. Nowadays, both of them play an important role towards our society and fortunately they cointegrated for offering us complex solution for a better quality of life.

The dynamic of everyone's daily life has changed drastically in the past years and as a consequence, more and more people suffer from mental health issues. They provoke obvious alterations on both personal and work-related plans, so a solution for this represents a primary necessity.

We usually refer to artificial intelligence as a set of algorithms that can imitate the human thinking process. By adapting the field of psychology to one of AI's branches, the present solution demonstrated that these algorithms can be used for developing a complex application which can improve people's life. This merging process was possible because cognitive behavioural therapy techniques were proved to be efficient during in-person session as well as integrated in online exercises.

As a final remark, the solution presented in the current paper has been found effective in improving different types of mental health issues. Giving the fact that the application can also detect if a user has serious psychological problems, it can be admitted that there is a low probability that it can cause additional harm to the patient's behaviour.

In conclusion, the developed chatbot accomplished the initial objectives and it can be considered a safe solution for managing and treating mental health issues.

References

[1] A. Vaidyam, H. Wisniewski, J. Halamka, M. Kashavan and J. Torous, "Chatbots and Conversational Agents in Mental Health: A Review of the Psychiatric Landscape," The Canadian Journal of Psychiatry, Vol 64, Issue 7, 2019, pp. 456-464. [Online]. Available: https://journals.sagepub.com/doi/full/10.1177/0706743719828977.

[2] K. H. Ly, A.-M. Ly and G. Andersson, "A fully automated conversational agent for promoting mental well-being: A pilot RCT using mixed methods," 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S221478291730091X.

[3] T. W. Bickmore, S. E. Mitchell, B. W. Jack, M. K. Paasche-Orlow, L. M. Pfeifer and J. O'Donnell, "Response to a relational agent by hospital patients with depressive symptoms," 2010. [Online]. Available: https://doi.org/10.1016/j.intcom.2009.12.001.

[4] N. Kathirvel, "Post COVID-19 pandemic mental health challenges," 2020. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7507979/.

[5] "National Alliance of Mental Illness," [Online]. Available: https://www.nami.org/mhstats.

[6] K. Cherry, "What Is Cognitive Behavioral Therapy (CBT)?," 16 May 2022. [Online]. Available: https://www.verywellmind.com/what-is-cognitive-behavior-therapy-2795747.

[7] "Cognitive Behavior Therapy Techniques," [Online]. Available: https://cogbtherapy.com/cognitive-behavior-therapy-techniques.

[8] "Part 6: Cognitive Restructuring to Change Your Thinking," [Online]. Available: https://cogbtherapy.com/cognitive-restructuring-in-cbt.

[9] B. Shikatani, M. M. Antony, J. R. Kuo and S. E. Cassin, "The impact of cognitive restructuring and mindfulness strategies on postevent processing and affect in social anxiety disorder," August 2014. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0887618514000887.

[10] A. Cuncic, "Understanding Cognitive Restructuring," 1 July 2020. [Online]. Available: https://www.verywellmind.com/what-is-cognitive-restructuring-3024490.

[11] "How To Make a Web Application Using Flask in Python 3," 17 April 2020. [Online]. Available: https://www.digitalocean.com/commu nity/tutorials/how-to-make-a-web-application-using-flask-in-python-3.

[12] "The 500 Most Frequently Used Words on Twitter," 8 June 2009. [Online]. Available: https://techland.time.com/2009/06/08/the -500-most-frequently-used-words-on-twitter/.

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