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AUTOMATIC ANALYSIS OF X (TWITTER) DATA FOR SUPPORTING DEPRESSION DIAGNOSIS

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Abstract: *Depression is an increasingly common problem that often goes undiagnosed. The aim of this paper was to determine whether an analysis of tweets can serve as a proxy for assessing depression levels in the society. The work considered keyword-based sentiment analysis, which was enhanced to exclude informational tweets about depression or about recovery. The results demonstrated the words used in the posts most often and the emotional polarity of the tweets. A schedule of user activity was mapped out and trends related to daily activity of users were analyzed. It was observed that the identified X (Twitter) activity related to depression corresponded well with reports on persons with depression and statistics related to suicidal deaths. Therefore, it could be construed that people with undiagnosed depression express their feelings in social media more often, looking, in this way, for help with their emotional problems.*

Keywords: *Twitter (X), tweet analysis, depression, data cleaning, data analysis.*

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INTRODUCTION

According to the World Health Organization (WHO), depression is the most common illness worldwide and the leading cause of disability. Over 260 million people worldwide suffer from depression, and over 800,000 people lose their lives every year due to suicides. It has been found that untreated depression is the main reason of suicides among teenagers, and suicides are the second leading cause of death in people aged 15-29 (WHO, 2017).

Mild symptoms of depression, which are often ignored, should not be neglected as very often they are harbingers of much more serious problems. The latter sometimes require hospitalization or even lead to attempted suicides (Halfin, 2007). Moreover, early diagnosis of depression is crucial as psychosocial treatment is especially effective in cases of mild depression. Unfortunately, over 50% of people suffering from this disease are undiagnosed. The lack of resources, lack of trained health care workers, and social stigmatization associated with mental disorders are the main barriers to effective care.

In 2020, the problem of depression worsened as the COVID-19 pandemic started. Multiple studies have shown that the lockdown related to COVID-19 has significantly impacted not only the economic and social aspects of peoples' life, but also the mental health of many. It was found that the rates of depression, anxiety, posttraumatic stress disorder (PTSD), and stress symptoms greatly increased during COVID-19 in comparison to earlier statistics, especially among females, youths, and low education groups (Xiong et al., 2020).

The widely accepted methods of treatment for medium and severe depression include psychology therapies (Cognitive Behavioral Therapy – CBT or Interpersonal Therapy – IPT) and medicines (selective serotonin reuptake inhibitors – SSRIs or tricyclic antidepressants – TCAs). While it has been found that after six months of treatment, the remission rate of depression is higher than 65% (Sinyor, Schaffer, & Levitt, 2010), over 50% of people suffering from this disease remain undiagnosed despite these ways of depression treatment. Current methods of identification, support, and treatment of clinical depression are considered ineffective, however, there is a greater need to improve the techniques of identifying depression rather than the methods of its treatment.

At present, many scientific institutions are investigating modern methods of identifying depression; it was hypothesized that depression could be identified from analyzing posts made on social media, with reliable statistical results. People with mental health disorders face stigmatization, and often prefer to talk about their problems through social networking sites rather than with their relatives or friends.

The aim of this research was to investigate whether it was possible to support a diagnosis of depression gleaned from automatic analysis of data, obtained from social networks, namely Twitter. Behavioral patterns regarding the activity of Twitter users related to depression and suicidal ideation were found and analyzed.

SOCIAL MEDIA

Social media allow users to create online content, exchange information, share their ideas or interests. Availability of mobile communication all over the world, as well as the increase of worldwide use of the Internet influences significantly the number of users of social media.

Currently over 45% of the world population belong to virtual communities and networks (Islam et al., 2018; Bachrach et al., 2012). According to data collected by Data Reportal (datareportal.com), BankMyCell (bankmycell.com) and Statcounter (gs.statcounter.com) there are 4.48 billion social media users worldwide, and this number increased over two-fold since 2015. The increase of the number of social media users since 2015 is presented in Figure 1 (Dean, 2022).

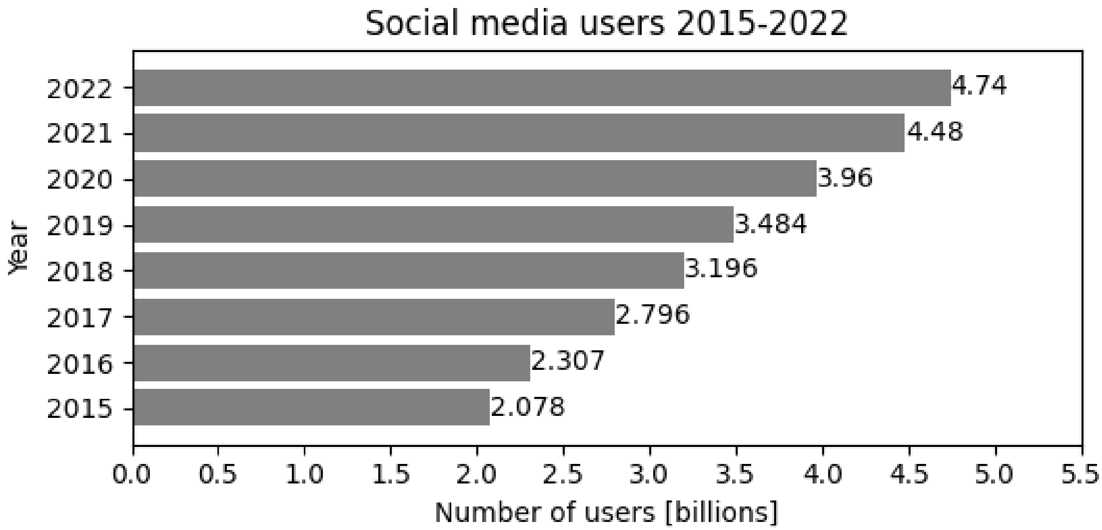

Figure 1. Number of social media users (2015-2022)

Among most often used social media are Facebook, Instagram and Twitter. The number of users of main social media is presented in Figure 2 (Dixon, Jul 26, 2022).

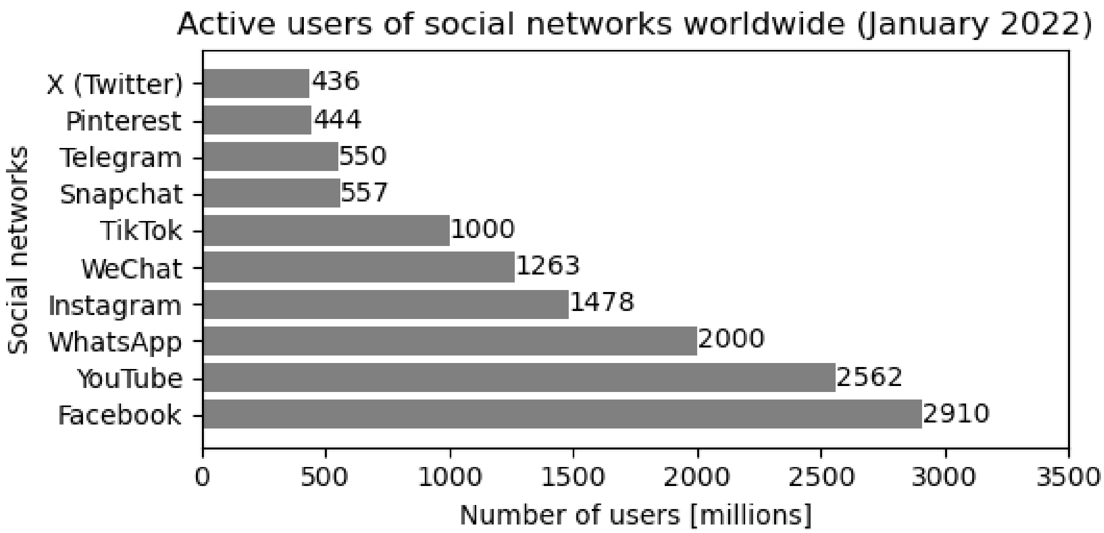

Figure 2. Use of social media in 2022

In recent years the number of people using platforms such as Facebook, X (Twitter) or Instagram to express their opinions, talk about their feelings and share their experiences have been increasing with every year. This makes social media platforms valuable resources to collect data about the society, including the state of publics' mental health (Mitchell, Hollingshead, & Coppersmith, 2015; Preoţiuc-Pietro et al., 2015; Conway, & O'Connor, 2016; Ernala et al., 2018; Mazuz, & Yom-Tov, 2020).

Platform X, formerly known as Twitter, is one of the social media platforms that allows for 'microblogging'; registered users may send or answer to so called 'tweets' – short text messages up to 280 characters, displayed on their public profile and visible to other accounts observing that profile. Twitter also allows for 'tagging' keywords or phrases by making use of so called 'hashtags' (# sign before the word or phrase). Users can write short messages on their profiles via direct website interface, SMS or mobile applications. Twitter is also a very popular means of communication amongst celebrities, politicians, businesses, diplomats and journalists to name a few. At present, most of public institutions, corporations, journals, and other organizations maintain official Twitter profiles as part of their online presence. Twitter users may read posts of persons with similar interests or similar problems, whilst at the same time maintaining a degree of anonymity.

The number of Twitter users accounts reported in 2022 was equal to 396.5 million what accounts for 8.85% of the worldwide social media users. The growth in the number of users is presented in Figure 3 (Dixon, Oct 6, 2022) and the distribution of Twitter users worldwide by age group (April 2021) is shown in Figure 4 (Dixon, Mar 29, 2022).

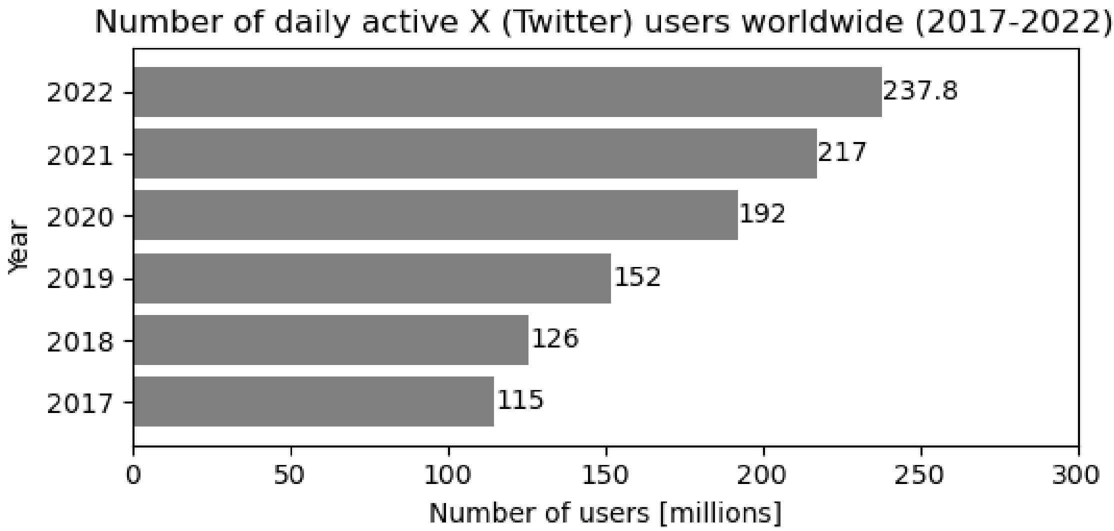

Figure 3. Increase in the number of X (Twitter) users in years 2017-2022

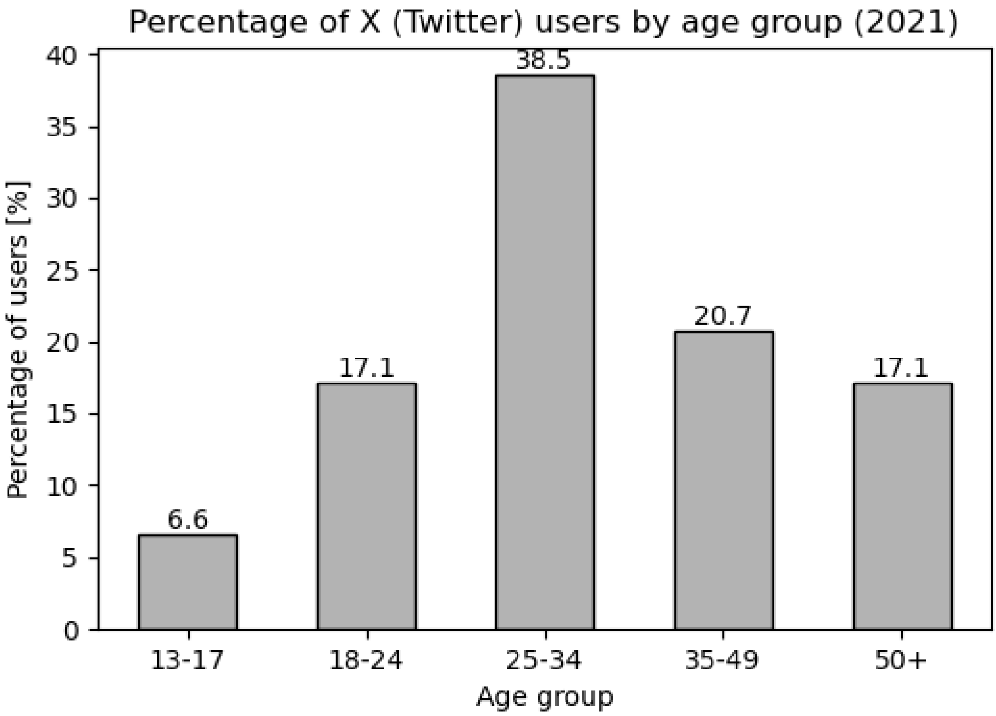

Figure 4. Distribution of X (Twitter) users by age groups

The ability of social media users to maintain anonymity makes such people more willing to share their problems with others without fear of stigmatization or other 'real world' repercussions. Such problems can include otherwise private physical and mental health disorders including depression. This observation suggests that Twitter can potentially provide a useful tool for surreptitiously observing social trends and data collected.

DEPRESSION

According to Oxford dictionary definition depression is "a medical condition in which a person feels very sad, anxious and without hope and often has physical symptoms such as being unable to sleep." (Oxford University Press, 2022). Nowadays depression, also known as major depressive disorder, is a common problem all over the world. According to World Health Organization (WHO) over 264 million persons worldwide suffers from this disease (WHO, 2017), which is considered as the fourth most serious health problem. Around 800000 people each year commit suicide. It has been found that not treated depression is the main reason of suicides among teenagers (Mann et al., 2005). The statistics showing the increase in terms of depression rates from 2017 to 2022 worldwide, in European countries and in USA are presented in Figures 5-7 (Alltucker, & Price, 2018; Dattani, Ritchie, & Roser, 2022; Depression Rates by Country, 2022; Depression Rates by State, 2022).

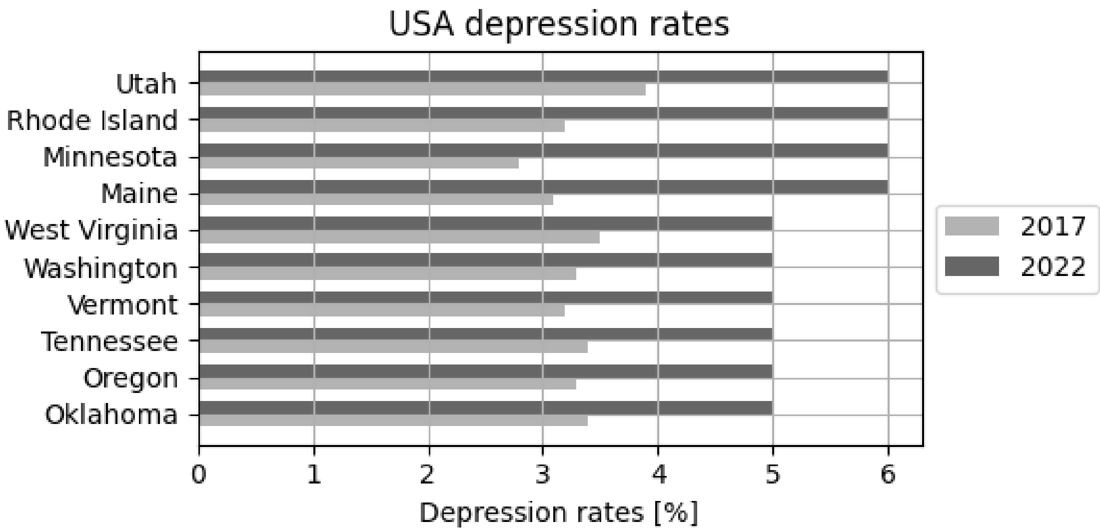

Figure 5. Comparison of depression rates in USA between years 2017 and 2022

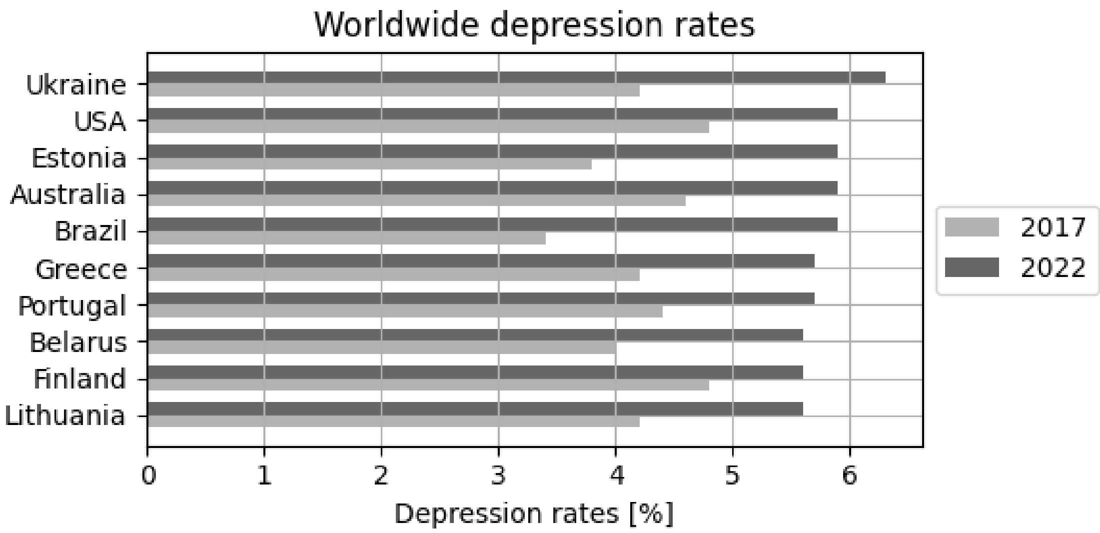

Figure 6. Comparison of depression rates worldwide between years 2017 and 2022

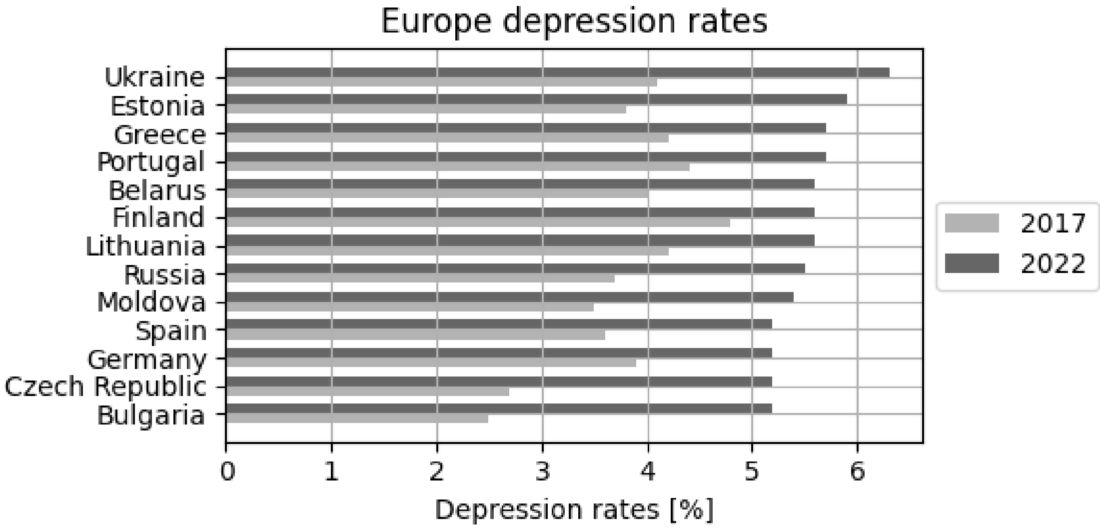

Figure 7. Comparison of depression rates in Europe between years 2017 and 2022

Depression can be classified into three categories depending on the number and severity of symptoms: mild, moderate or severe. Symptoms of depression include emotional ones, like feeling of sadness or loss of interest in activities once enjoyed, but also physical, such as headache, aching muscles and joints, gastric problems or decreased vision. There are several methods for self-diagnosis of depression, such as Beck Depression Inventory BDI (Beck, Steer & Brown, 1996), Center for Epidemiologic Studies Depression Scale CES-D (Radloff, 1977), Patient Health Questionnaire – 9 PHQ-9 (Kroenke, Spitzer & Wiliams, 2001) and Geriatric Depression Scale GDS (Yesavage et al., 1982). The most widely used diagnostic evaluation tools are DMS-5 (American Psychiatric Association, 2015) and ICD-10 (WHO, 1993). DSM-5 defines 9 criteria of depression: (1) depressed mood, (2) diminished interest or pleasure, (3) significant changes in appetite or weight, (4) insomnia or hypersomnia, (5) psychomotor agitation or retardation, (6) fatigue or loss of energy, (7) feelings of worthlessness and guilt, (8) diminished ability to concentrate, and (9) recurrent thoughts of death or suicide. ICD-10 scale is very similar to DMS-5 but gives the possibility to assess the severity of depression depending on the number of symptoms. However, it is common to misdiagnose depression (Eichstaedt et al., 2018; Dedovic, & Ngiam, 2015).

Since 2020 we can observe increase of the cases of mental illness, including depression, related to COVID-19 pandemic (Li et al., 2020; Liu et al., 2020). Most often appearing problems are the increased despair or anxiety, feeling of guilt, posttraumatic stress disorder (PTSD), but also insomnia, larger alcohol and drug consumption or increase in smoking (Li et al., 2020; Xiong et al., 2020).

A number of studies has been conducted in various countries all over the world to evaluate the prevalence of depression and generalized anxiety disorder (GAD) during the COVID-19 pandemic. Research done in Ireland showed that 20% of examined sample of 1041 Irish representatives suffered from GAD and 22.8% were diagnosed positively for depression (Hyland et al., 2020). In Hong Kong study a group of 500 respondents was questioned, out of which 19% reported depression, 14% reported anxiety and 25.4% reported deterioration of mental health since pandemic (Choi, Hui, & Wan, 2020). Study conducted in the US showed that the prevalence of depression symptoms in the USA was more than 3-fold higher during COVID-19 compared with the numbers collected before the COVID-19 pandemic (Flegal, Graubard, Williamson, & Gail, 2007).

It has been found that people with depression very frequently use social media (Neira & Barber, 2014; Lin et al., 2016; Rasmussen et al., 2020). Among social media users with depression changes in social relationships, activity and language were observed (DeChoudry, Counts, & Horvitz, 2013, April; Zulkarnain, Basiron & Abdullah, 2020). The main linguistic markers of depression are the focus on oneself and using first person singular pronouns (Chung & Pennebaker, 2007; Mowery et al., 2017; Preotiuc-Pietro et al., 2015), using words related to negative emotions, associated with depression anxiety and illness (Nguyen et al., 2014; Jung, Park & Song, 2017; Guntuku et al., 2017), as well as frequent use of absolute words such as “always”, “never”, “entire” (Al-Mosaiwi & Johnstone, 2018).

PRIOR AND RELATED RESEARCH

In countries with high income levels, people with depression are often not properly diagnosed, and others who do not have such a disorder are too often misdiagnosed and are prescribed antidepressants. In addition, in Western societies it is believed that a well-mannered person should be able to control his or her emotions, including depression, and it is believed that a person should be able to cope with depression.

Often, people who notice the symptoms of depression in themselves, are ashamed to admit to their relatives or tell the doctor about it. In this case, there is a chance that such a person, especially young, wanting to vent their emotions will use social media to anonymously talk about his or her problems and find people who would show understanding. During the annual meeting of the Association of Psychological Sciences in San Francisco (Rettner, 2018), the results of research conducted on over 500 students were presented, which showed that people with symptoms of depression described themselves as heavily dependent on social media, much more often than people without any symptoms, and they had often very active Twitter accounts with over 300 people watching them.

Another study, conducted between 2009 and 2010 with a group of students at the University of Wisconsin-Madison, showed that over thirty percent of those identified as having a depression according to the PHQ-9 scale that participated in the study, showed symptoms of depression in Facebook posts (Moreno, Christakis, Egan, Jelenchick, Cox, Young, Villiard, & Becker, 2012). The aim of this study was to identify the links between the visible symptoms of depression on Facebook and the symptoms of depression reported by them during the clinical trial. Public Facebook profiles of students from two universities have been checked for shared references regarding depression. Profiles have been classified as indicating symptoms of depression or not indicating the symptoms of depression. Participants completed an online survey that allowed to determine the scale of depression according to PHQ-9. The analyzes examined the relationship between the result of the questionnaire and the indicators of depression symptoms for people showing and not showing symptoms of depression. The mean PHQ-9 score for people without any symptoms was 4.7 (SD = 4.0), the mean PHQ-9 score for depressive symptoms was 6.4 (SD = 5.1, p = 0.018).

Since it was noticed that there is a correlation between depression and the content of posts made available by people with depression through social networking sites, the researchers began to work on the possibilities of using social media to diagnose depression. Social media content from platforms provide a lot of information about the users' moods, feelings, and behaviors. This data reflect people's mental health in their everyday life. Therefore Geographic Information System (GIS) and social media data mining are more and more often used tools enabling investigation of the spatiotemporal pattern of mental stress (Jahanbin, & Rahmanian, 2020; Coppersmith, Dredze, & Harman, 2014; De Choudhury, Counts, & Horvitz, 2013 May).

Automatic analysis of posts from social networking sites potentially provides methods for early detection of depression. If an automated process could detect elevated depression symptoms in a user, the person could be directed to a more in-depth assessment and to be provided with further support and treatment (Guntuku et al., 2017).

Platforms most often used in data mining and analysis for depression detection are Facebook (Islam et al., 2018; Eichstaedt et al., 2018), Twitter (De Choudhuryet al., 2013 April; Collingwood, 2016; Tadesse, Lin, Xu, & Yang, 2020; Reece et al., 2017) and Reddit (Tadesse, Lin, Xu, & Yang, 2019; Cacheda et al., 2019). Results from the analysis of Facebook data show accuracy of depression detection at the level of 60-70% (Islam et al., 2018; Eichstaedt et al., 2018). Study combining data from Facebook and Twitter for depression detection reported similar values, namely 57% accuracy, 67% precision and 56% recall (Aldarwish, & Ahmad, 2017). Much better results were reported for analysis of Twitter posts showing the accuracy from 70% using crowdsourcing (De Choudhury et al., 2013 May), 85% accuracy with combination of Naive Bayes classification and Multiple Social Networking Learning (Collingwood, 2016; Reece et al., 2017) to 91.7% accuracy of the algorithm based on Principal Component Analysis and Support Vector Machine 10-fold cross validation (Tadesse et al., 2020). A number of papers report the use of sentiment and emotional analysis on Twitter data (Coppersmithet al., 2014; De Choudhury et al., 2013 April; Go, Bhayani, & Huang, 2009; Zhou, Tao, Yong, & Yang, 2013). It was found that the use of sentiment analysis, along with percentage of depressed tweets, increases the precision and recall of detecting depression (Jamil et al., 2017). De Choudhury et al. (April 2013) and Jamil et al. (2017) extracted features from the tweets of people with depression to increase the detection accuracy of algorithms using sentiment analysis. DeChoudhury (April 2013) built a depression lexicon of terms that are likely to appear in posts of persons talking about depression. Jamil et al. (2017) used the percentage of depressed tweets and the information about the self-indication with depression of the tweet author in order to include or delete such user from the training set, what increased the detection accuracy. Detecting depression from Spanish tweets using sentiment and emotion lexicons was also used by Leis et al. (Leis et al., 2019).

Early studies on depression detection by tweets analysis used relatively small data samples, with less than 500 users. Coppersmith et al. (2014) have used n-gram language models, Armstrong in his study (Armstrong, 2018) used topic models, and Orabi et al. (Orabi et al., 2018) used deep learning models such as 1-dimensional convolutional neural networks (CNN) and bidirectional long short-term memory (BiLSTM). Tsugawa et al. (Tsugawa et al., 2015) showed that the useful features for the prediction model are frequencies of word usage, together with topic modeling. They used the radial kernel SVM classifier for the dataset of 81 participants out of the 209 collected samples from questionnaires. The reported accuracy of the classifier was equal to 69%.

However some methods, based on lexicon, that were used in the early attempts to detect depression from social media posts have become outdated since nowadays many Twitter users very often use emojis (Chen et al., 2018). N-grams used for instance by (Coppersmith et al., 2014) are not useful in classifying tweets since there may appear a problem with classifier training when considering words that are not used in tweets (Barbosa, & Feng, 2010). Instead of n-grams the use of microblogging features (hashtags, emoticons, re-tweets, comments) to train an SVM classifier was suggested in (Pak, & Paroubek, 2010). They showed that the use of microblogging features resulted in higher accuracy.

Various supervised classifiers were used in studies concerning depression detection from social media posts, including support vector machine (SVM) (Aldarwish, & Ahmad, 2017; Sadeque, Xu, & Bethard, 2018), naïve Bayes (Pratama, & Sarno, 2015; Arora, & Arora, 2019), Support Vector Regression (SVR) (Arora, & Arora, 2019). Very good results with accuracy and F1-score over 90% were achieved in depression detection using Neural Networks (Lin, Hu, Su, Li, Mei, Zhou, & Leung, 2020; Tadesse et al., 2020; Zogan et al., 2022).

Li et al. (2020) proposed the CorExQ9 algorithm to analyze the COVID-19 related stress symptoms based on Twitter users posts at a spatiotemporal scale. The CorEx algorithm combined with clinical stress measure index (PHQ-9) allowed for reducing human interventions and human language ambiguity in social media data mining. They showed a strong correlation between stress symptoms and the number of increased new COVID-19 cases for some major U.S. cities.

Summing up the overview of works related to depression detection in social media posts based on sentiment analysis it can be concluded that data analyzed include text, emoticons and emojis (Cheng & Tsai, 2019; Abid, Li & Alam, 2020). There are two main approaches: rule-based and machine learning based sentiment analysis (Babu & Kanaga, 2022). According to (Salas-Zarate et al., 2022) the most commonly used lexicon-based feature extraction techniques are n-grams, bag of words, word embedding, tokenization, stemming and part-of-speech (POS) tagging. Classification techniques analyzed posts can be divided into 3 groups: binary (positive or negative), ternary (positive, neutral or negative) and multiclass distinguishing between different emotions (Jabreel & Moreno, 2019; Tao et al., 2019) or depression levels (Al Asad et al., 2019). Classification methods used in various research projects include Machine Learning techniques like SVM, Naïve Bayes, Multinomial Naïve Bayes, Random Forest, Ensemble vote classifier, or KNN (Ruz, Henriquez & Mascareno, 2020; Kumar, Sharma & Arora, 2019; Gaikwad & Joshi, 2016), as well as Deep Learning techniques like LSTM, BiLSTM, CNN and GRU (Chen et al., 2018; Cheng & Tsai, 2019; Bouazizi & Ohtsuki, 2016). Considering reported accuracy results the most effective are approaches using deep learning techniques and multiclass classification (Babu & Kanaga, 2022).

METHODS

It has been shown that sentiment analysis is an effective tool in emotion detection based on analysis if social media posts. Most of the research related to depression detection in social media is performed on labeled datasets. The goal of this research is to verify if there exists correlation between the results of sentiment analysis and the statistics related to depression. Positive correlation can indicate the usefulness of automatic posts' emotion polarity analysis for supporting depression detection and diagnosis. Therefore the research question was stated:
RQ: Is there a correlation between the number of negatively marked tweets extracted by sentiment analysis and statistics related to depression, mental illness and suicidal tendencies for the given region?
In the implementation of the system for tweets analysis MongoDB and Python programming language were used. In order to enable Python and MongoDB interaction PyMongo module was used. The process of the implementation was divided into the following steps: keyword selection, data acquisition, data rectification and analysis, and data visualization.

Keywords selection

Crucial step in obtaining proper data for analysis was selection of keywords related to depression and similar emotional states. Keywords selected were English words due to the popularity of this language in the world. However it limited the research results mostly to English-speaking countries. The keywords were detected based on the words used previously in related research (Chen et al., 2018; Movery et al., 2017; Nguyen et al., 2014; Jung et al., 2017) and based on their emotional score defined in the NRC Word-Emotion Association Lexicon (EmoLex) (Mohammad, & Turney, 2013). The choice of keywords was also influenced by the expressions used in PHQ-9 questionnaire ("suicidal", "feeling down", "feeling bad about yourself") and their synonyms.
Data was collected in three sessions. In the first session used keywords were: *depression, anxiety, suicide, suicidal*. Second session of data gathering included words such as: *broken, sad, afraid, alone*. Third phase combined words from sessions 1 and 2 with addition of word *depressed*. For the analysis all tweets containing at least one of the keywords were taken.

Data acquisition

Three 24-hour readings were performed at 2-day intervals. The total number of tweets collected was 3,015,617. Each measurement was analyzed separately, some of the data was also summarized collectively. For the purpose of data acquisition application *apps.twitter.com* was used, that allows the user to generate a token and a private key that enable to read tweets using API. A script was written in Python for reading tweets containing predefined keywords and saving them in json format. Collected data was stored as collections in MongoDB database.

Data rectification and analysis

For further analysis the rectification of collected data was performed. Stored tweets were grouped based on the keywords and then the sentiment analysis was performed. Sentiment analysis, or opinion mining, is a field of study that analyzes people’s opinions, attitudes and emotions towards given entities. It uses a natural language processing (NLP) technique, that can determine if the examined text is positive, negative or neutral (Liu, 2015). For this purpose Python script using TextBlob library was written. TextBlob library enables to perform sentiment analysis based lexicon-based approach, using Natural Language ToolKit (NLTK) that gives an access to a large number of lexical resources. As a result the polarity and subjectivity of the analyzed text are returned. The range of polarity is [-1;1], where -1 indicates negative and 1 positive sentiment. Subjectivity is given in range [0;1] and the higher the score, the more personal is the analyzed opinion (Shah, 2020). For the analysis the tweets of sensitivity above 0.5 were selected and next their polarity was analyzed.

While analyzing tweets, there was a risk that a significant part of the results could be distorted by entries of organizations dealing with the prevention of depression, containing keywords such as *depression* or *suicidal*. Such entries should not be considered in terms of analysis in this project. Also, entries from people who have dealt with the problem and talk about their struggles with the disease may affect the correctness of the results. To partially reject this false data, it was decided to conduct a sentiment analysis. Thanks to such analysis, it was possible to determine which tweets are positive, negative and neutral. By rejecting positive and neutral tweets, it is possible to get rid of some of the data not related to the project's goal. This method allows for better data selection, but does not guarantee avoiding mistakes related to entries containing irony or hyperbolization, e.g. "Tomorrow is Biology test, I will probably kill myself". In order to achieve greater accuracy of the data, it would be necessary to carry out a more detailed analysis of entries and classification based on machine learning, using more features to classify entries.

Based on the emotional markers collected tweets were grouped into positive (polarity > 0), neutral (polarity = 0) and negative (polarity <0). At this stage the content of the database was limited to the following elements: user name, tweet text, time of entry, location and polarity. Tweets with no location defined were rejected from further analysis. Finally, data selection was performed in order to gather the following information: 1) distribution of the locations with largest number of tweets, 2) distribution of the locations with largest number of tweets with negative polarity, 3)most active users, 4) most active using posting tweets with negative polarity. Location of selected tweets was converted to geographical coordinates so in the process of visualization it was possible to display the most often appearing locations on the world map.

Data visualization

In order to make the obtained data more readable and understandable for readers, it was presented using different visualization methods. Data on the percentage shares of individual phrases and the percentage of negative, positive or neutral tweets, were presented using pie charts generated in Anaconda programming environment.

Another method of graphical representation of data are maps showing the intensity of the number of posts in a given region of the world. Such a map allows to intuitively understand which cities in the world have tweeted the most actively in terms of topics related to the searched keywords. To display the data on a map, the Folium library for the Python programming language was used. Aggregated data was used, using the latitude and longitude of each of the 20 cities as locations, city name as name, and number of tweets as frequency. The bubble radius for a given location is proportional to the number of tweets added from that location.

The next visualization method used was tornado charts for presenting comparison of tweets distribution in US states and statistics related to major depression episodes and suicidal deaths in the United States of America.

The fourth method of data visualization used were bar charts showing the number of tweets added in hourly time intervals. For each dataset, two such charts have been created for the two most popular locations, UK and US, and refer to the local time of this locations.

The last used method for data presentation was generating word clouds in order to show the frequency of use of the given keyword.

RESULTS

In the three 24-hour sessions 3,015,616 tweets were analyzed, 520,829 of which were assigned with the known location. Graphical distribution of the emotional markers percentage for each session is shown in Figure 8. Table 1 shows the number of tweets collected in each session.

Table 1. Characteristics of tweets collected in 3 sessions

	All tweets	Negative	Neutral	Positive	Tweets with known location
Session 1	373167	120146	127478	125543	67773
Session 2	1071171	549918	227142	294111	183669
Session 3	1571278	765995	371998	433285	269387

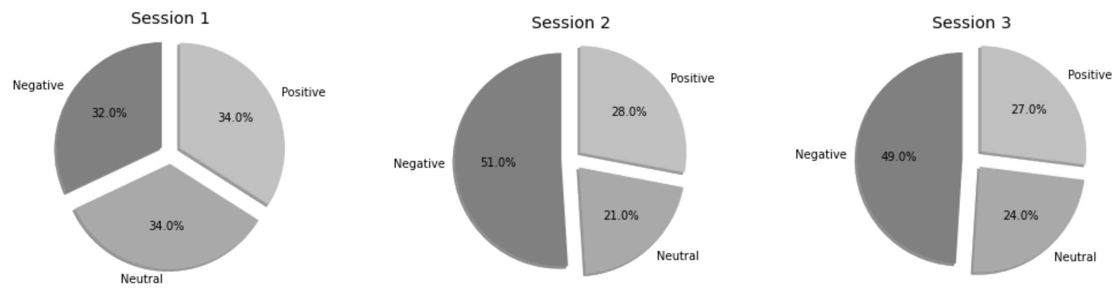

Figure 8. Distribution of the emotional markers percentage for each session

Session 1

In session 1 373,167 tweets were analyzed. Of the tweets with the keyword *depression*, only 29% (18,747 out of 64,490 entries) had a negative character. In the case of tweets containing the word *anxiety*, the disproportion was even greater. As many as 58% of entries were classified as positive, 24% as neutral and only 18% as negative.

Reading the entries containing this keyword, it could be observed that it is often used by health organizations, units dealing with the prevention of depression and by public profiles of medical facilities and research centers. In the case of this keyword, focusing only on entries classified as negative can bring particularly great benefits when it comes to improving the quality of data. In the case of tweets containing the *suicide* keyword only 23% of tweets were identified as positive, 31% as negative and 46% as neutral. In the case of entries containing the word *suicidal*, there is a noticeable clear advantage of entries with negative markings - 91% of entries. The neutral and positive entries take on the values of 5% and 4% respectively.

Based on the above data, it is possible to observe the proportion of negative tweets to all tweets for given keywords. The highest negative character could be observed for the word *suicidal* (91%), successively for the word *suicide* (31%), *depression* (29%), and the weakest negative character was noticeable for the word *anxiety* (18%). Because the percentage share of tweets containing the given word was not equal, it was decided to check the percentage share of keywords after rejecting positive and neutral tweets. The largest share of all tweets classified as negative had entries containing the keyword *suicidal* (40%). Subsequent entries include the words: *depression* (21%), *anxiety* (20%) and *suicide* (19%) (Figure 9).

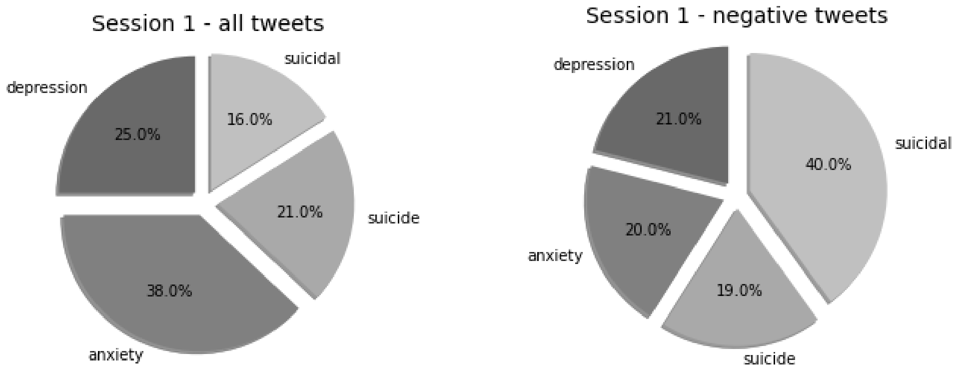

Figure 9. Share of keywords in all analyzed tweets and in tweets with negative emotional character for session 1

Based on the tweeds that had correct location data, the places in the world with most active users were found. The process of checking city activity for the set of tweets identified as negative by the sentiment analysis was performed. In this case London was the most active city. Then, the next eight most active cities are in the United States. On the map with negative tweets (Figure 10) greater activity on the north-eastern side of the United States can be noticed, and smaller in the south-west of the map. Also visible are single active locations in Africa - Lagos in Nigeria, India - Mumbai and two cities in Australia - Sydney and Melbourne.

Figure 10. Intensity map of tweets with negative character containing keywords for session 1

Session 2

The total number of tweets collected during the second session was equal to 1,071,171. The most frequent tweets contained the word sad (90,052, 47% of all entries) and alone (304,149, 29% of all entries). The words broken and afraid had respectively 14% and 10% shares. After the sentiment analysis, 294,111 positive entries were received (51%), 227,142 neutral (28%) 549,918 negative (21%). It means that this set of data in case the used terms is much more "negative" than keywords used in the first session. This may be due to the fact that in the previous set of data the words used were more formal, thus more often used by institutions than by private individuals.

Based on the above data, it is possible to observe the proportion of negative tweets to all tweets for given keywords. The largest share of all tweets classified as negative had entries containing the keyword sad (61%), next was the keyword broken (17%), afraid (12%) and alone (10%) (Figure 11).

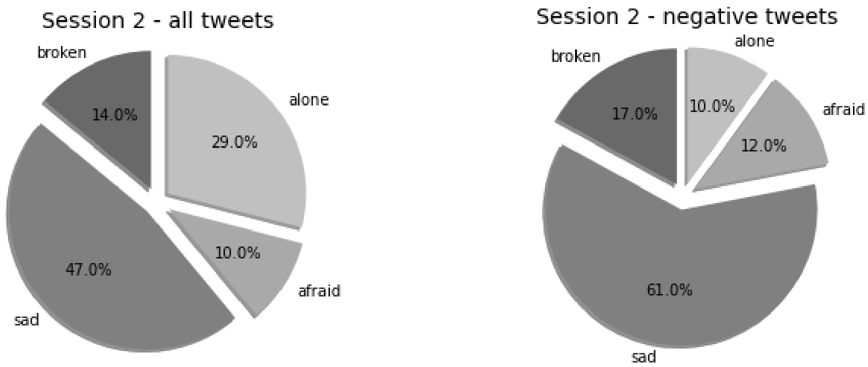

Figure 11. Share of keywords in all analyzed tweets and in tweets with negative emotional character for session 2

On the basis of this data, a map was created, which using bubbles shows the activity of users from a given location. The map shows that the most tweets were read from the Great Britain and the United States. In the United States, the highest concentration of bubbles is also visible, i.e. many locations close to each other have been classified as the most active. There is also a lot of activity in Nigeria, South Africa and Pakistan. It can be assumed that such disproportion in tweets flowing from English-speaking countries to other locations results from the fact that the search keywords were in English (Figure 12).

Figure 12. Intensity map of tweets with negative character containing keywords for session 2

Session 3

During session 3 1,571,278 tweets containing predefined keywords were collected. The most commonly used keywords in session 3 were: *anxiety* (34%), *alone* (19%) and *suicide* (13%). The words *broken* and *afraid* were present in 8% of cases, while *depressed* and *depression* in 6% of cases. The word *suicidal* is a negligible part of all entries. Of all the data collected, after sentiment analysis, 49% were classified as negative tweets, 27% were positive and 24% were neutral. After rejecting positive and neutral tweets, the largest share of all tweets classified as negative had entries containing the keyword *sad* (46%). Next were entries containing the word *suicide* (17%), *broken* (11%), *afraid* (10%) and *alone* (9%). The words *anxiety*, *depression* and *suicidal* were negligible (Figure 13).

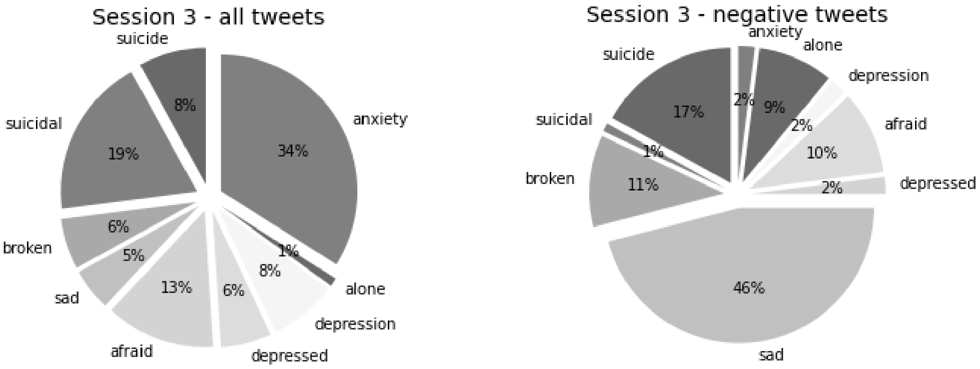

Figure 13. Share of keywords in all analyzed tweets and in tweets with negative emotional character for session 3

Then, based on tweets that had valid location data, an analysis was made of which places in the world were most active during measurements. The most active city turned out to be London, from which 10,678 entries were made, followed by Los Angeles with 8,467 tweets. The map shows that again most tweets were read from the Great Britain and the United States (Figure 14).

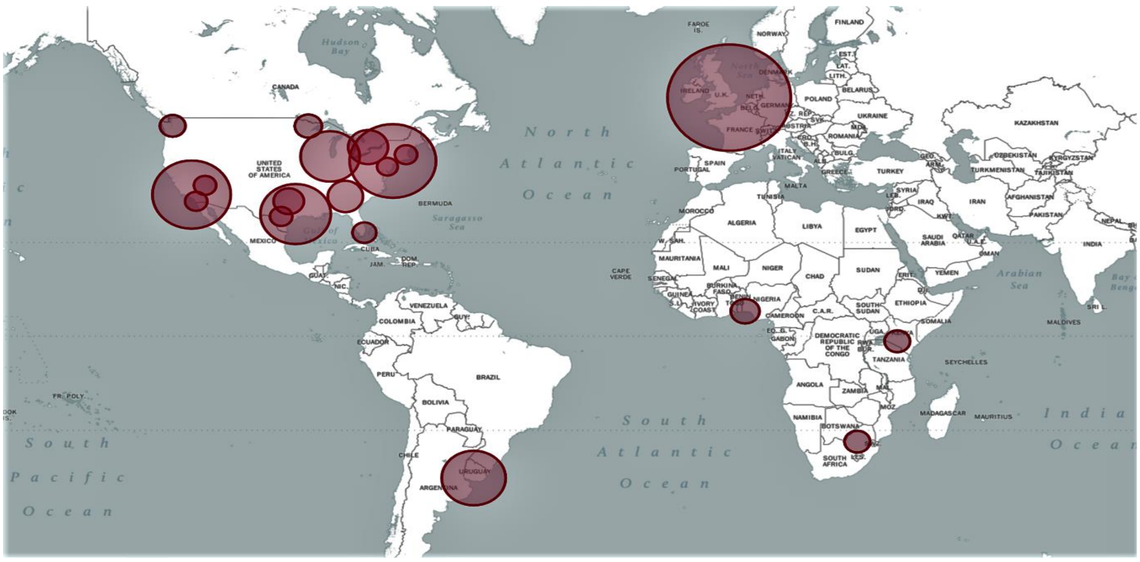

Figure 14. Intensity map of tweets with negative character containing keywords for session 3

Summary of the results

Total number of gathered tweets in the three session was equal to 3,015,617. For all collected data, after sentiment analysis, 48% of tweets were found to be negative, 28% positive and 24% neutral. The largest negative character could be observed for the word *sad* (79.5% of this word usage), 77.5% for *broken*, 76% for *suicidal* and 76% for *afraid*. A much weaker negative character could be observed in the case of the word *alone* (30.5% of all occurrences of this word), *depression* (27%) and *anxiety* (21.5%). The percentage share of each keyword in all the three sessions classified as negative (Figure 15), neutral (Figure 16) and positive (Figure 17) are presented in the form of pie charts and word clouds.

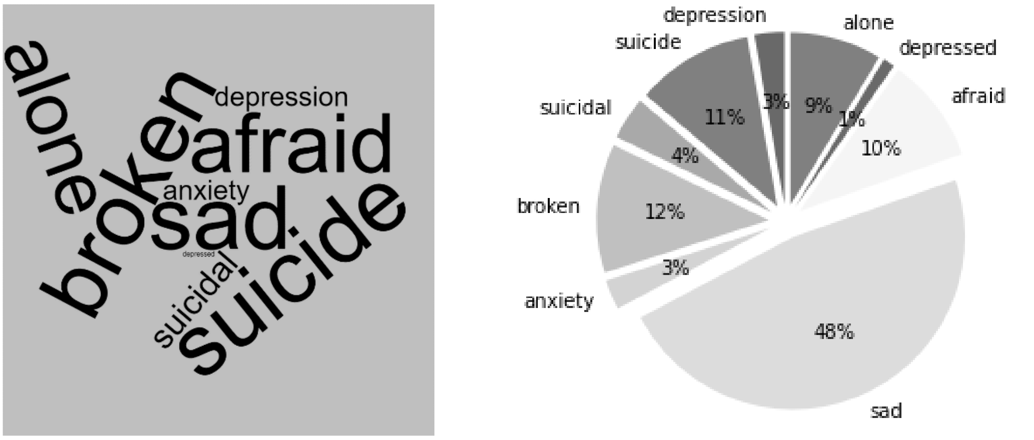

Figure 15. Share of keywords in tweets with negative character

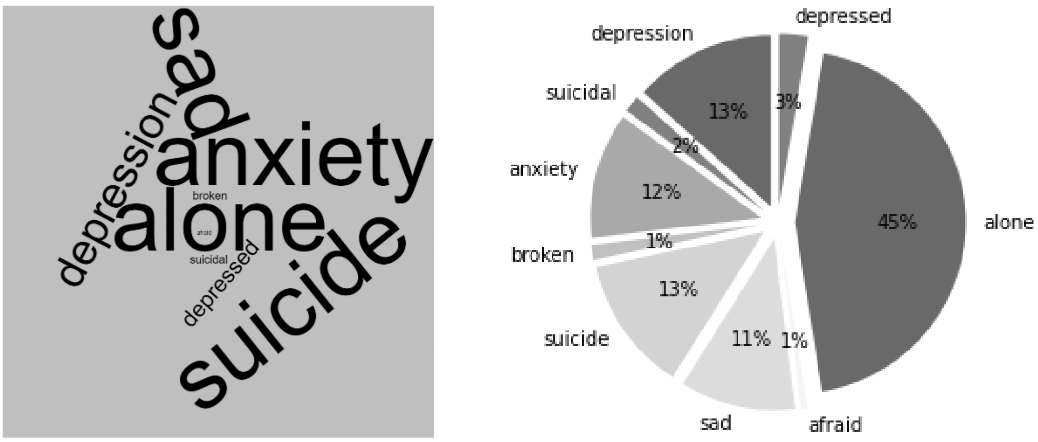

Figure 16. Share of keywords in tweets with neutral character

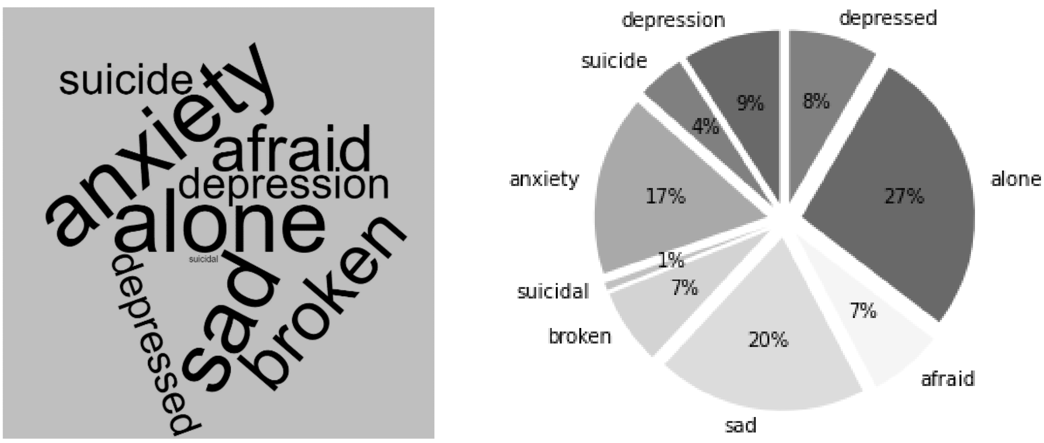

Figure 17. Share of keywords in tweets with positive character

It has been observed that often tweets containing the terms depression or anxiety are positive entries from organizations and pro-health institutions. With the help of sentiment analysis, it was possible to partially reduce this type of data by deleting data classified as positive and neutral. After this procedure, the number of entries made available by the most active users decreased by 55%. For some of the entries (around 18%), the location was read. For these tweets, the analysis of the most active locations was carried out. Users from London in the UK turned out to be the most active ones, followed by users from different cities in the United States. Also, a large number of tweets came from places like Nigeria, Kenya, South Africa and Pakistan.

For the final stage of the results analysis only the negatively marked tweets from the USA were selected in order to verify the validity of the research question stated. The percentage of all tweets and negative tweets in the ten states of the USA with highest Tweeter activity for all 3 sessions is presented in Figure 18.

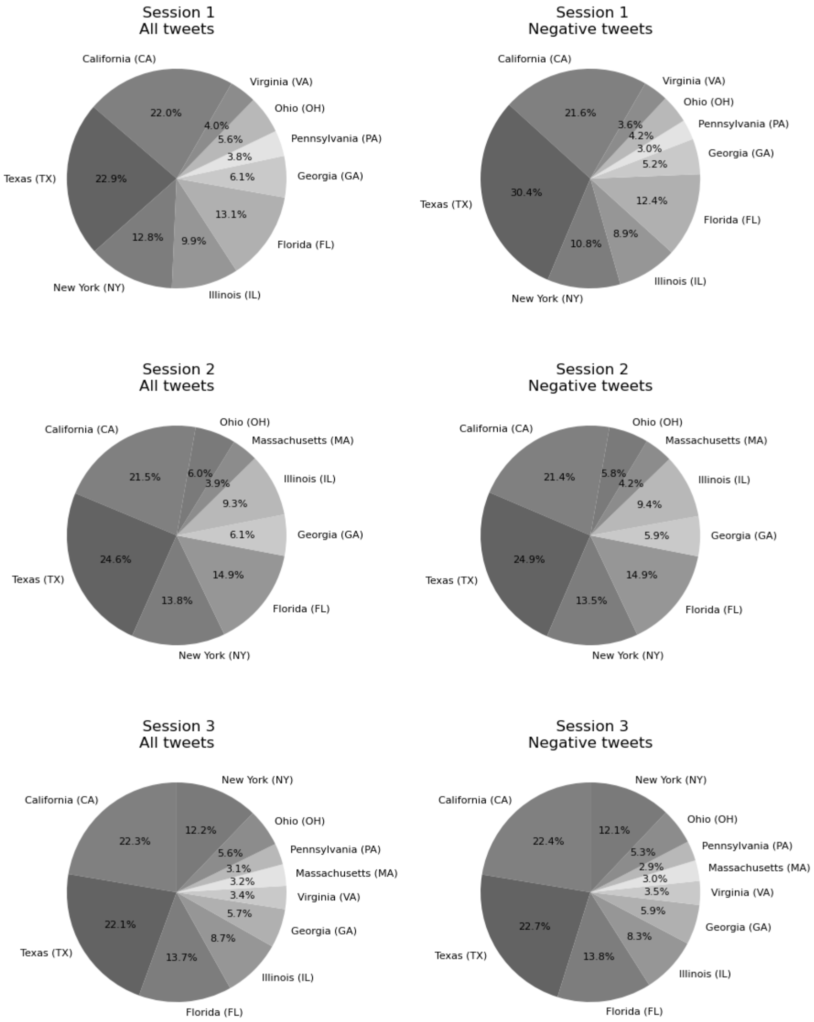

Figure 18. Percentage share of tweets with known location extracted in the 3 sessions for the 10 US states with largest Tweeter activity

DISCUSSION

The distribution of Twitter/X activity related to depression in the United States of America (Figure 19) was compared with available official screening statistical data concerning: Major Depressive Episodes (MDE) among young people who reported no medical help, any mental illness (AMI) among people who reported no medical help (Nguyen, Hellebuyck, & Halpern, 2017), and with numbers of suicidal deaths in 2017 (Alltucker & Price, 2018). In all cases 8 out of first 10 US states overlap with the list of 10 tweeting states from the research (Table2).

Table 2. Comparison of the nnumber of negative tweets with suicidal deths statistics (Alltucker & Price, 2018) and screening results for persons with MDE and AMI who reported receiving no medical help (Nguyen, Hellebuyck, & Halpern, 2017)

Presented research		**MDE with no medical help**		**AMI with no medical help**		**Suicidal deaths**	
US State Code	**No. of tweets**	**US State Code**	**MDE**	**US State Code**	**No. of people (x1000)**	**US State Code**	**Suicidal Deaths**
CA	14457	**CA**	**47000**	**CA**	**5919**	**CA**	**4294**
TX	13124	**TX**	**32000**	**TX**	**3657**	**TX**	**3488**
FL	8426	**NY**	**28000**	**NY**	**321**	**FL**	**3143**
NY	7451	**OH**	**21000**	**FL**	**3094**	**PA**	**1970**
IL	5218	**IL**	**20000**	**PA**	**2165**	**OH**	**1707**
GA	3480	**FL**	**19000**	**OH**	**2140**	**NY**	**1679**
OH	3229	MI	19000	**IL**	**1930**	**IL**	**1415**
MA	1904	**PA**	**16000**	NC	1783	**GA**	**1409**
VA	1342	NC	14000	MI	1652	NC	1373
PA	1113	**MA**	**11000**	**GA**	**1635**	MI	1364

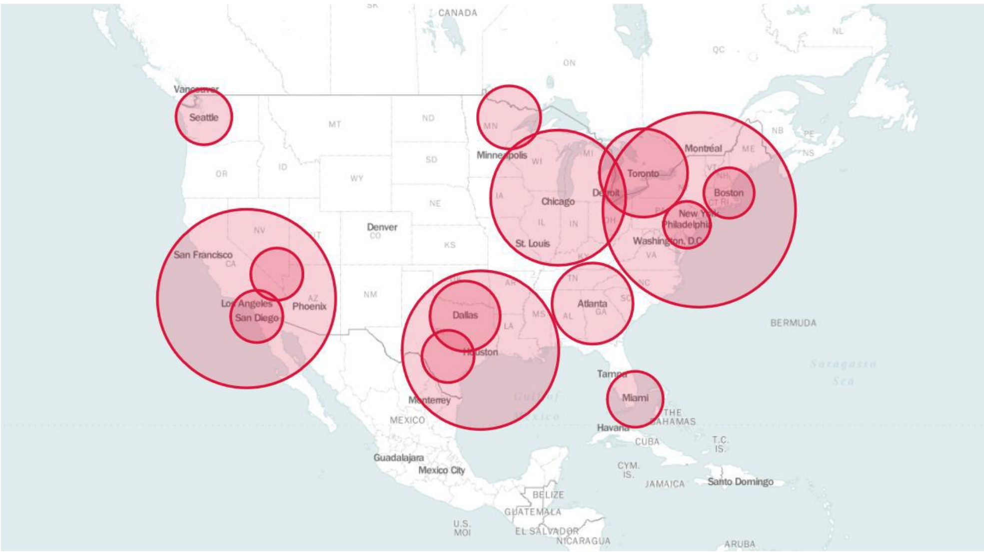

Figure 19. USA intensity map of tweets with negative character containing keywords defined for all sessions

It was observed that tweets identified as related to depression corresponds well with US suicidal deaths statistics, as well as with reports considering persons with depression who did not receive professional medical help or received it only partly. Moreover, the numbers related to persons suffering from mental illness who did not receive professional help also correspond well with the presented tweets distribution.

The numbers of negatively marked tweets were also compared with the results of screening reports related to depression and self-harm and suicidal thoughts (Nguyenet al., 2017). The correlation coefficient was calculated for the sets containing number of screeners diagnosed with moderate, moderate-severe and severe depression (Figure 20), as well as with screeners reporting having suicidal thoughts more than half of the days and almost every day (Figure 21). The results are presented in Table 3. It can be observed that the sets are highly correlated.

Table 3. Correlation coefficients for negative tweetss numbers and screening results in US states

	Moderate depression	**Moderate-severe depression**	**Severe depression**	**Suicidal thoughts over half of the days**	**Suicidal thoughts almost every day**
Correlation coefficient	0,90	0,93	0,95	0,92	0,94

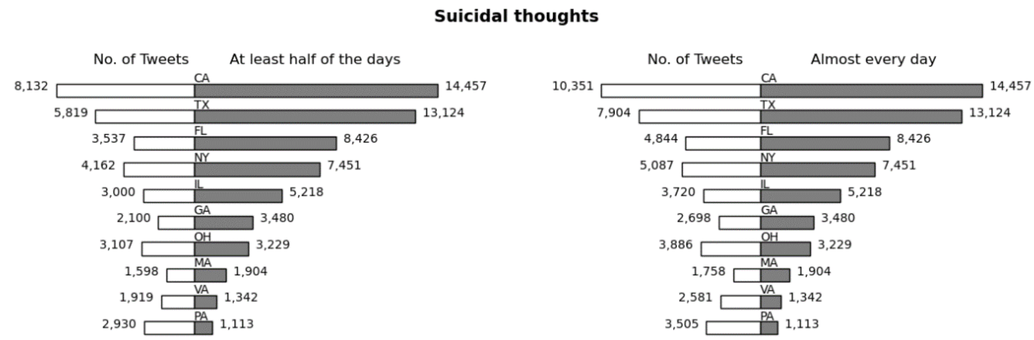

Figure 20. Comparison of the number of negative tweets in top 10 US states and number of persons reporting suicidal thoughts in screening tests

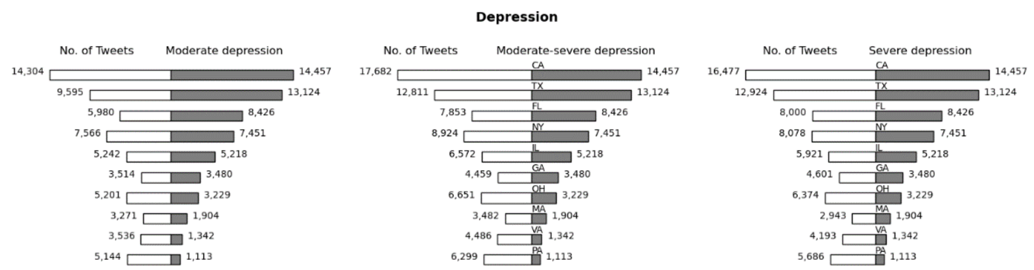

Figure 21. Comparison of the number of negative tweets in top 10 US states and number of persons reporting depression

It could be then construed that people with undiagnosed depression and suicidal thoughts are more often expressing their feelings in social media, looking in this way for help with their emotional problems. This thesis is confirmed by the statistics presented in (The Clinical Committee, 2019) showing that people with depression use social media more often (Pantic, 2014) and 55% of persons with high depression symptoms engage in over 30 social media sessions per week. Also people with suicidal tendencies post often on social media, informing about their feelings, expressing suicidal thoughts (Sueki, 2013; Gunn & Lester, 2015). The review presented in (Zubair, Khan & Albashari, 2023) suggests that using social networks is correlated with psychological problems such as anxiety, depression, insomnia and sense of mental deprivation. This statement is in accordance with the presented results of the study, confirming that people with depression, mental disorders and suicidal tendencies post about their mood, feelings and thoughts, what can be detected using sentiment analysis.

An additional analysis was performed to look into daily activity of users tweeting about sadness and depression. There was a decrease in activity during the night hours between 1 and 6 in the morning – corresponding to generally lower Twitter activity in the night, stable high level of activity during the day, with a maximum in hours 20-21 (Figure 21).

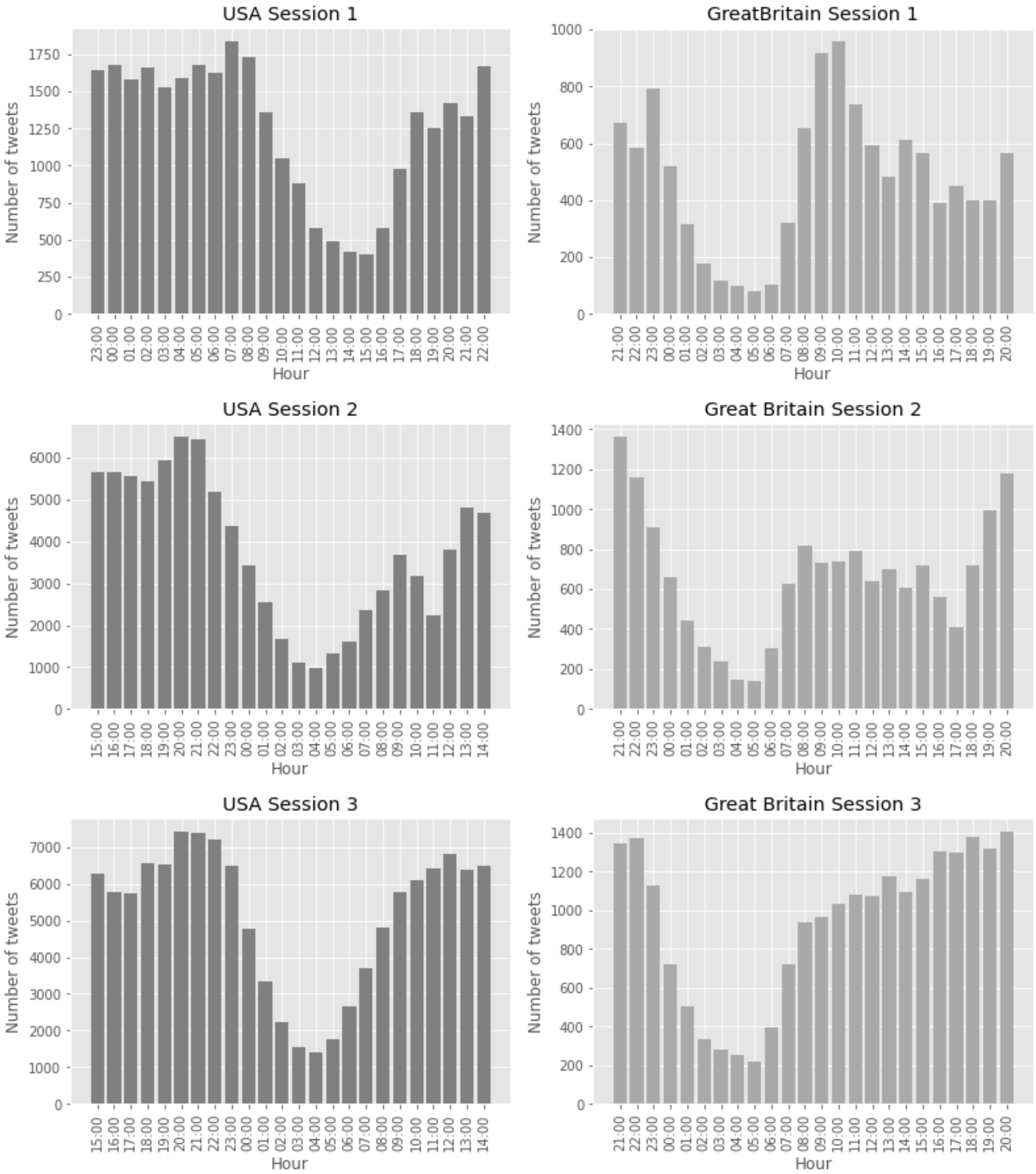

Figure 22. Daily activity of Twitter users in USA and UK during 3 sessions

CONCLUSIONS

Depression is an increasing health problem in the world. It can be called a plague despite the availability of effective treatments for this disease. About 50% of people who suffer from depression are undiagnosed. At present, it is important to find as many depression patterns as possible to improve the identification process. The aim of the work was to assess if analysis of tweets can serve as a proxy for assessing depression level in the society. Performed research allowed to identify certain patterns of Twitter users' activity, adding posts about depression, suicides, sadness or loneliness, to broaden the general knowledge of depression and provide additional data that could help to prevent this disease. The work focused primarily on Twitter activity in Great Britain and the United States. This is due to the use of keywords in English. To extend the work, it would be necessary to use translations of given words for a larger group of languages.

It should also be taken into account that in some African countries social networks are not used due to the lack of access to computers and smartphones, and in Asian countries such as Korea, China, social networks other than Twitter are more popular. For tweets from the United States, the activity maps were compared with a map of the percentage of people with diagnosed depression and a correlation was observed. Collected data allow to observe certain tendencies related to the activity in social media of people who provide entries on subjects related to depression, sadness, fears, or loneliness. Of these people, potentially, some may suffer from undiagnosed depression. Understanding the patterns of their behavior on the Internet may contribute to improving the ability to recognize and diagnose this disease, and it may also enable the introduction of systems for detecting persons who are at risk. This method could be improved and expanded so that the amount of data obtained is greater and the results more reliable.

To improve the accuracy of the results it would be necessary to conduct a more targeted research on tweets from people diagnosed with depression but not treated, healthy people and people diagnosed with depression during the treatment process. Tweets from an extended time span from selected individuals should also be analyzed in order to uncover differences between the activity of sick, healthy and treated people.

IMPLICATIONS FOR THEORY AND APPLICATIONS

The results indicate that analysis of posts in social networks, if carefully performed, can serve as an indication of society level of depression. It is probable that this approach could be extended to other diseases, especially of psychological nature. In the past Twitter data has been shown to be a useful predictor of e.g. stock exchange prices (Bollen, & Mao, 2011). It indicates that it reflects population mood and emotions well, to an extent to it impacts decision making.

Considering these results, public institutions should invest in project that would deepen this understanding and extend to other social networks, which might be more appropriate for other populations and social challenges.

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