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ORIGINAL RESEARCH

# A review on recognizing depression in social networks: challenges and opportunities

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**Abstract**

Social networks have become another resource for supporting mental health specialists in making inferences and finding indications of mental disorders, such as depression. This paper addresses the state-of-the-art regarding studies on recognition of depressive mood disorders in social networks through approaches and techniques of sentiment and emotion analysis. The systematic research conducted focused on social networks, social media, and the most employed techniques, feelings, and emotions were analyzed to find predecessors of a depressive disorder. Discussions on the research gaps identified aimed at improving the effectiveness of the analysis process, bringing the analysis close to the user's reality. Twitter, Facebook, Blogs and Forums, Reddit, Live Journal, and Instagram are the most employed social networks regarding the identification of depressive mood disorders, and the most used information was text, followed by emoticons, user log information, and images. The selected studies usually employ classic off-the-shelf classifiers for the analysis of the available information, combined with lexicons such as NRC Word-Emoticon Association Lexicon, WordNet-Affect, Anew, and LIWC tool. The challenges include the analysis of temporal information and a combination of different types of information.

**Keywords** Depressive disorders · Affective computing · Mental health · Sentiment analysis · Emotion recognition · Social media · Social networks · User behavior

## 1 Introduction

The area of data science has emerged and expanded towards meeting the growing volume of data and their required computational analysis capability. Approaches and algorithms of machine learning and data mining enable the extraction of information from large complex data sets. Such approaches have been reoriented to this new environment and used for both data interpretation and creation of predictive models in financial (Idrees et al. 2019), political (Jungherr 2016), medical (Cazzolato et al. 2019), and criminal (Huang et al. 2018) domains. Regarding their use in the areas of physical and mental health, data science methodologies have also enabled the extraction of large sets of data for identification of patterns and accumulation of significant knowledge (Cortés et al. 2015; Giuntini et al. 2019; Herland et al. 2014).

Although widely discussed, depression is popularly known as the disease of the century, as it has already been a concern pointed out by researchers. For instance, CDC (2001) and Luoma et al. (2002) highlighted depression affected approximately 27 million Americans and could be related with over 30,000 suicides each year. In a projection for the next 20 years (Mathers and Loncar 2006), depression would be the leading cause of disability in high-income countries, as the United States, and in 2014 it is one of the most costly worldwide diseases (Centers for Disease Control and Prevention and others 2014). Despite its overwhelming impact on human conditions, its high co-morbidity with suicidal ideation and behavior, and its high financial cost, the investment in evaluation and intervention strategies have been too little. In a study about the economic return of investment in the treatment of depression, Chisholm et al. (2016) have shown that in countries such as Brazil, it would

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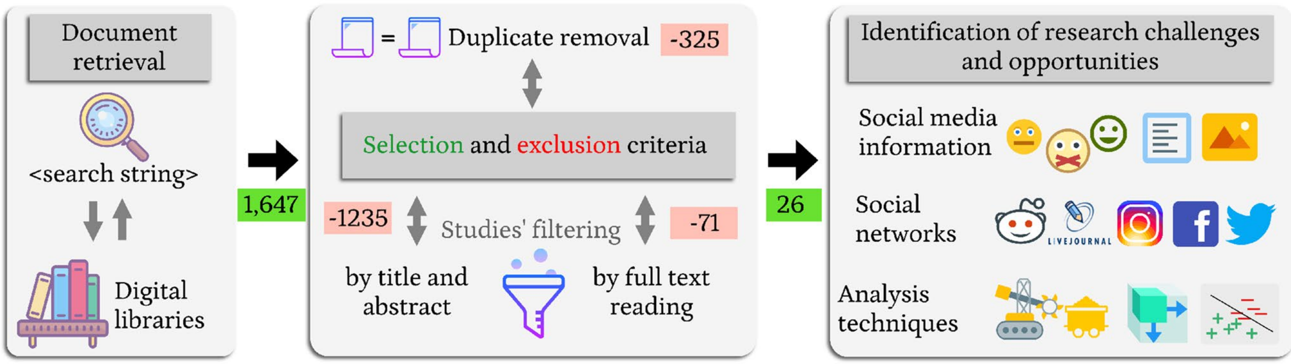



**Fig. 1** Summary of the current study. The green boxes show the number of studies moving from one step to the next. Red boxes inform the number of excluded studies by each criterion

be necessary a contribution of 86% or more of the current investment to deal with this issue.

According to RC et al. (2003) and González et al. (2010), although several primary care programs have been designed for detection and treatment, the majority of Americans with symptoms of depression did not receive treatment or the treatment was insufficient. Additionally, minority ethnic groups, such as Mexican Americans and African Americans, are significantly less likely to receive anti-depression therapies than other ethnic groups. In 2017, the World Health Organization (WHO) reported the total number of people living with depression worldwide was 322 million, and the estimated total number of people living with depression increased 18.4% between 2005 and 2015 (World Health Organization and others 2017).

Data analysis techniques can automatically identify disturbances, based on indicators and symptoms of depressive disorders (American Psychiatric Association and others 2013). Abnormal patterns in behavior can be recognized in online social networks through data mining techniques, sentiment analysis, and recognition of emotions (Moreno et al. 2011). Although the current performance of predictive models is considered suboptimal, reliable models eventually could detect depressive mood disorders early, thus, paving the way for fast interventions and promotion of relevant public health solutions.

The work in Guntuku et al. (2017) presents a previous review of the use of social media for the detection of depression and mental illness. The authors focused on the Facebook and Twitter social medias. Although their findings are promising, they only considered the analysis of depression and did not discuss the sentiments, emotions, and other disorders that usually come along, as discussed in this paper.

The current paper investigates the state-of-the-art of how sentiment and emotion analysis approaches can identify depressive disorders in social networks. Figure 1 summarizes the steps and goals of our literature review process. Subsequent to retrieving the studies from the leading digital libraries, we employed selection and exclusion criteria and obtained the studies which were further analyzed. We aim to answer the three following questions:

1. Which types of *social media* information were adopted for the identification of depressive mood disorders?
2. Which *social networks* were explored in the identification of depressive mood disorders?
3. What *state-of-the-art techniques* have been employed for the identification and classification of depression for each *social media*?

**Paper outline.** The remaining parts of the paper are organized as follows: Section 2 describes the relevant background on depressive disorders. Section 3 presents the method applied in the systematic review that includes search strategy, selection criteria, and data extraction. Section 4 provides the systematic review results and an overview of studies conducted, the social media and social networks employed, and the sentiments and emotions analyzed. Section 5 discusses research questions and opportunities in the area of recognition of depressive mood disorders from a computational and psychological point of view. Finally, Sect. 6 gives the conclusions.

## 2 Background—depressive disorders

The World Health Organization and others (2017) characterize depressive disorders as follows: composed of sadness, loss of interest or pleasure, feelings of guilt or low self-esteem, sleep or disturbed appetite, feeling tired, and lack of concentration. Besides, depression can be long-lasting or recurrent, substantially impairing an individual's ability to function at work or school or deal with daily life. In its most severe form, depression can lead to suicide.

The American Psychiatric Association recommends the use of the most recent edition of the Diagnostic and Statistical Manual of Mental Disorders (American Psychiatric Association and others 2013), widely known as DSM-V, for the evaluation and diagnosis of the depressive status by mental health professionals. Duailibi and da Silva (2014) argue that major depressive disorder is composed of at least five of the following symptoms, present for at least two weeks, and which represent changes in the prior functioning of the individual. Since at least one of the symptoms are (1) depressed mood or (2) loss of interest or pleasure.

- Depressed mood in most days, almost every day (e.g., feeling sad, empty or hopeless) by subjective observation or by third parties;
- Accentuated decrease in pleasure or interest in all or almost all activities most of the day, almost every day;
- Significant loss or gain in weight without being on a diet (e.g., change in more than 5% of body weight in a month), or increased or decreased appetite almost every day. In children, consider the inability to present the expected weight gains;
- Insomnia or hypersomnia almost every day;
- Psychomotor restlessness or retardation almost every day;
- Fatigue and loss of energy almost every day;
- Feeling of worthlessness or excessive or inadequate guilt, almost every day;
- Reduced ability to think or lack of concentration or indecision, almost every day;
- Recurrent thoughts of death, recurrent suicidal ideation without a specific plan, or attempted suicide or specific plan to commit suicide.

Additionally, the authors emphasize that it is possible to add information in the diagnostic process, called specifiers. These specifiers allow a better characterization and prognosis of each case:

– **Anxiety characteristics:** Demands the presence of at least two of the following symptoms on most days: feeling tense; restless; difficulty concentrating due to concerns; fear that something terrible will happen; control loss feelings. In cases where two symptoms are present, it is considered mild; three is moderate; four or five is moderate to severe; and with motor agitation is severe.
– **Mixed characteristics:** At least three of the following symptoms of mania and hypomania should be present almost every day during an episode of major depressive disorder: elevated mood, high self-esteem; more speech than usual or greater speech pressure; escape from ideas or subjective experience that thoughts are accelerated; increased energy for a specific activity (social, work, school or sexual); excessive involvement in activities of high potential for harmful consequences, such as excessive purchases, sexual indiscretion, unplanned investment; sleeplessness.
– **Melancholic characteristics:** At least one of the following symptoms: loss of pleasure in most activities; and lack of reaction to usually enjoyable activities. Also, three (or more) of the following symptoms: depressed mood characterized by profound dejection; worsens symptoms in the morning; terminal insomnia; restlessness or psycho-motor retardation; significant loss of appetite or anorexia; excessive or inappropriate guilt.
– **Atypical characteristics:** Mood reactivity (improvement with stimuli) or two (or more) of the following symptoms: increased appetite or weight gain; hypersomnia; feeling of weight in the legs or the arms, besides lack of energy; a lasting pattern of sensitivity to social rejection, resulting in significant social prejudice.
– **With psychotic delusions or seasonal patterns:** delusions related to depression or depressive disorder only in specific periods of the year.

This complex set of symptoms has been associated with a substantial loss in quality of life indicators. We usually observe a cause of significant distress or impairment in social, occupational, or even other essential areas of the individual's life (Duailibi and da Silva 2014). Moreover, studies examining the relationship between depression and poverty conditions have indicated that the prevalence of depression may represent economic impacts similar to natural disasters, civil conflicts, or abrupt changes in society. The study seems to indicate that the higher the scores obtained in the depression's indicator were related to a less amount of time devoted to work, lower total expenditure, and reduced investment in education. However, tobacco consumption was higher in this population (Barrett et al. 2019).

The American Psychiatric Association and others (2013) is offering several "emerging measures" for future research in clinical evaluations for a standardized and accurate diagnosis. These measures were developed to be administered at the initial interview with the patient and monitor the progress of the treatment. They should also be used in research and evaluation for potentially improving clinical decision-making, and not as the sole basis for a clinical diagnosis. The PROMIS Emotional Distress–Depression form,[1] for example, is a useful tool for the mental health professional to confirm the presence or absence of depressive disorder, as well as its level. The patient answers a set of eight questions on the frequency he/she has been bothered by a list of "negative

[1] Available online in http://www.dsm5.org/Pages/Feedback-Form.aspx.

feelings" during the last week. The choices of answers range among never, rarely, sometimes, often and always.

## 3 Method applied in present study

This section presents the method employed for the development of a systematic review on the identification of depressive mood disorders in online social networks. The procedure supported by Parsifal tool,[2], which follows the guidelines reported in (Barbara and Charters 2007) and a protocol was defined for the development of this review.

### 3.1 Search strategy

The following search string answered the three research questions reported in Sect. 1:

```
((sentiment ∗ ORemotion ∗ )
AND(depressionORdejectionORvalley
ORdoldrumsORprostrationORmegrim
ORlow − spiritedness)
AND(}}socialnetwork″OR
}}onlinecommunity ∗ ″OR}}socialmedia″))
```

The primary studies that identified depression in online social networks were retrieved, and the feelings and emotions recognized in the process, along with the techniques employed, were then obtained. The search was conducted in November 2018. The studies were collected in the following digital databases and with no restriction of publication period: ACM Digital Library, Compendex, IEEE Digital Library, ISI Web of Science, Science Direct, Scopus, Springer Link, and Taylor, and Francis Online. Specifically, at the Springer database, we chose to filter studies from the area of computer science only, due to the high number of studies returned without this filter, which was more than 10 thousand ones.

### 3.2 Selection criteria

After a systematic reading of the titles and abstracts of the studies, the inclusion criterion adopted was the selection of only primary studies that infer depression in social networks through the analysis of feelings and recognition of emotions. This only criterion guided the identification of studies that could provide direct evidence on the research questions. Studies that (1) do not deal with computational aspects, (2) do not characterize a primary study, (3) do not propose a computational approach or method that infers depressive disorders in online social networks, (4) are duplicate, that is, they have already been evaluated, were excluded.

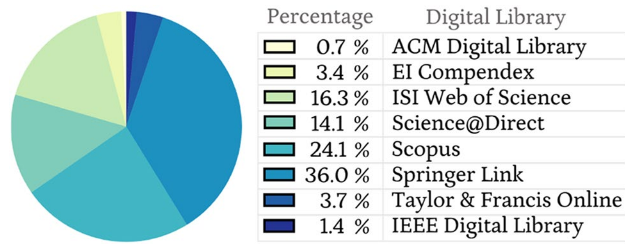



**Fig. 2** Portion of studies retrieved from each digital library considered in our work

### 3.3 Data extraction

After selecting the studies and obtaining the set of studies that had met the inclusion criteria, data were extracted through a complete reading of the selected studies. An extraction form with the following questions was defined: (1) To which social network was the study applied? (2) What social media were considered in the study? (3) Does the study identify emotions or feelings? If so, which ones? (4) Apart from depressive aspects, what other disorders are inferred by the study? (5) What is the main methodology employed?

## 4 Results

This section addresses the literature review conducted. First, we give an overview of the way the studies were obtained. We also present the exclusion criteria considered in this work. Each selected study is then presented, along with a brief description of its main objective. Since we are interested in studies regarding the recognition of depression in social networks, we introduce the social network and the information type used by the selected studies. Finally, we address the considered sentiments, emotions, and other disorders.

### 4.1 Overview of the studies

Figure 2 depicts the proportion of studies returned per digital database, according to the search string. A total of 1647 studies were obtained, most of which from Springer Link (36.1%), Scopus (24.1%) and ISI Web of Science (16.3%), followed by Taylor Francis Online (3.7%), El Compendex (3.5%), IEEE Digital Library (1.5%) and ACM Digital Library (0.7%).

Figure 3 shows the PRISMA diagram (Liberati et al. 2009), which covers all stages of the selection process,

[2] Available at parsif.al.

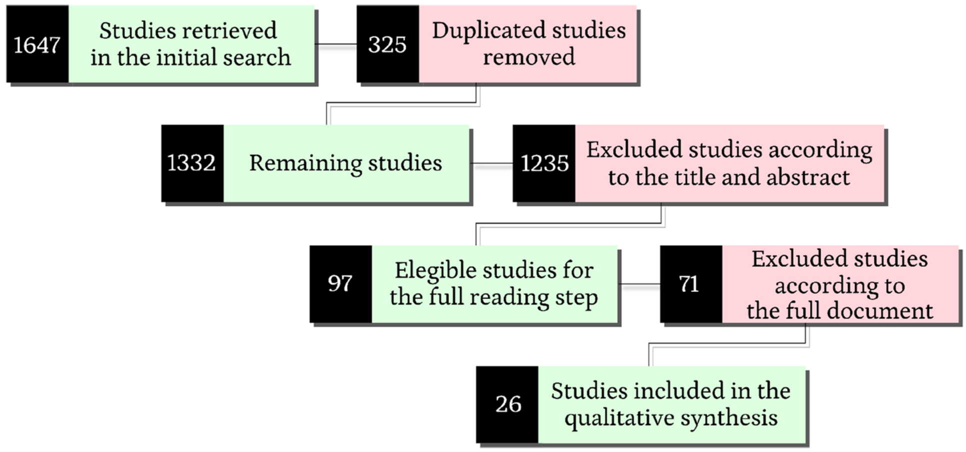



**Fig. 3** PRISMA flow of the literature review

following the methodology presented in Sect. 3. On the left side (green boxes) is the number of selected studies, and on the right side (red boxes), we show the studies removed in each step. Initially, 325 duplicate studies were removed. Duplication occurs because the study can be indexed in more than one digital base concomitantly. A total of 1235 studies were excluded from the 1332 selected ones, considering the title and abstract reading step, which resulted in only 97 studies eligible for a full reading. Other 71 studies that did not meet the inclusion criteria during the full reading phase were excluded from the 97 initially eligible ones, and only 26 primary studies were included in the qualitative synthesis.

We examined the studies towards answering the inclusion and exclusion criteria (described in Sect. 3.2). They were annually distributed as follows: 5 in 2013, 1 in 2014, 2 in 2015, 1 in 2016, 15 in 2017, and 2 in 2018. Table 1 shows the authors and the objective of each study. Table 2 summarizes the social networks, the type of media explored, the methods employed, the sentiments, emotions, and other disorders approached in each study considered in the review. We discuss each of these aspects in the next subsections.

## 4.2 Social networks used in the studies

Figure 4 shows the most used social networks detected in the studies considered in our review. Twitter is the most explored social network. Studies that rely only on Twitter as a data source are (De Choudhury et al. 2013a, b; Wang et al. 2013; Birjali et al. 2017; Guangyao Shen 2017; Vedula and Parthasarathy 2017; Lachmar et al. 2017). In their work, Hassan et al. (2017) combined Twitter with another local social network, and Jung et al. (2017) built their dataset combining data from Twitter, Blogs and Forum, and another local social network.

Seabrook et al. (2018) explore data from Twitter and Facebook, and the studies (Park et al. 2013; Wee et al. 2017; Polignano et al. 2017; Ophir et al. 2017) use only Facebook, which is the second most adopted social network. Facebook has a large number of features available, and it also allows the analyst to verify user behavior by verifying users' timeline information. Particularly for the behavior analysis area in the Psychology field, the provided information by Facebook allows a better understanding of depressive behavior, since it is possible to combine and merge different types of complex data. On the other hand, the experience of relying on Facebook can be challenging given that the corporation is continuously changing its privacy policies, which often requires periodic changes in the applications, making it harder to maintain an online solution for a long time without proper updates.

The works (Park et al. 2013; Leiva and Freire 2017; Park and Conway 2018) considered Reddit, which is a worldwide social network with communities of depression, anxiety, stress, and happiness. It enables studies focused on communities with specific themes, and its great advantage is that communities (called *subreddits*) use slightly more formal and structured English sentences as a way of communication. Such sentences ensures the development of scientific studies in the area of text analysis and natural language processing, since the pre-processing of the content becomes less tedious. Furthermore, the official Reddit API data collection is made easier compared to other social networks.

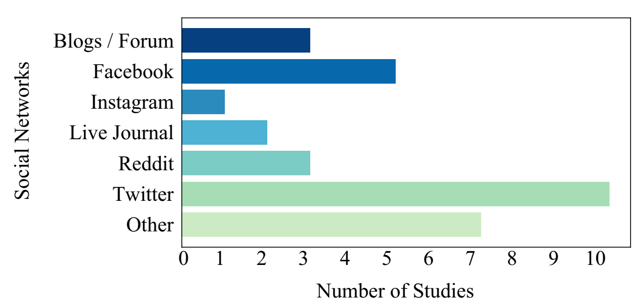



**Fig. 4** Social networks approached in the studies

**Table 1** Overview of the selected studies

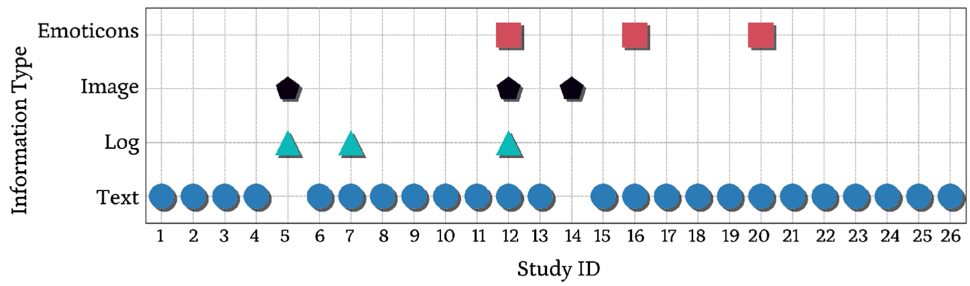
| ID | Authors | Objective |
|---|---|---|
| 1 | De Choudhury et al. (2013a) | Use of SVM classifier for checking Twitter posts that indicate depression and proposal a of metrics that measures the index of depression |
| 2 | Xu et al. (2013) | Proposal and evaluation of a new theory on the contagion of depression in social networks |
| 3 | Wang et al. (2013) | Application of data mining methods for the detection of depressed users in social networking services |
| 4 | De Choudhury et al. (2013b) | Exploration of the potential use of social media for the detection and diagnosis of depressive disorders |
| 5 | Park et al. (2013) | Development of a Web application that identifies features related to depressive symptoms on Facebook |
| 6 | Chomutare (2014) | Evaluation of text classification methods to identify patients with risk of depression |
| 7 | Semenov et al. (2015) | Investigation of methods and metrics published regarding the analysis of a community of depression in Russian social network VKontakte |
| 8 | Karmen et al. (2015) | Development of a method that detects symptoms of depression in free text |
| 9 | Tung and Lu (2016) | Investigation of text mining methods that analyze and predict depression trends in web postings |
| 10 | Park and Conway (2017) | Investigation of longitudinal changes in psychological states, which manifest themselves through linguistic changes in members of a community of depression |
| 11 | Birjali et al. (2017) | Search for feelings of depression in Twitter users' activities for the estimation of their depressive tendencies |
| 12 | Wee et al. (2017) | Demonstration of the interaction between depression and personality based on behavioral data from Facebook users |
| 13 | Nguyen et al. (2017) | Exploration of the textual evidence of online communities interested in depression |
| 14 | Reece and Danforth (2017) | Application of machine learning tools for a successfully identification of markers of depression in Instagram photos |
| 15 | Vedula and Parthasarathy (2017) | Observational study for the understanding of interactions between clinically depressed users and their ego-network, in contrast to a differential control group of normal users and their ego-network |
| 16 | Guangyao Shen (2017) | Timely depression detection via harvesting of social media data |
| 17 | Leiva and Freire (2017) | Analyses of messages that a user posts online during a time period and detect the risk of depression |
| 18 | Hassan et al. (2017) | Detection of a person's level through the extraction of emotions from the text |
| 19 | Fatima et al. (2017) | Use of user-generated content for the identification of depression and further characterization of its degree of severity |
| 20 | Polignano et al. (2017) | Description of an architecture model that identifies some warning scenarios of blue feelings in Facebook posts |
| 21 | Ophir et al. (2017) | Comparison of the traditional offline clinical picture of depression with its online manifestations, and exploration of unique features of online depression that are less dominant offline |
| 22 | Lachmar et al. (2017) | Examination of the public discourse of the trending hashtag #MyDepressionLooksLike towards a closely at how users talk about their depressive symptoms on Twitter |
| 23 | Cheng et al. (2017) | Exploration computerized language analysis methods can assess one's suicide risk and emotional distress in the Chinese social media |
| 24 | Jung et al. (2017) | Refining of an adolescent depression ontology and terminology as framework for analyses of social media data and evaluation of description logic between classes and the applicability of this ontology to sentiment analysis |
| 25 | Seabrook et al. (2018) | Report of associations between depression severity and variability and instability in emotion word expression on Facebook and Twitter across status updates |
| 26 | Park and Conway (2018) | Investigation written communication challenges manifest in online mental health communities focusing on depression, bipolar disorder, and schizophrenia |

In Reece and Danforth (2017), the authors conducted a study with the photo-sharing social networking Instagram, which poses some bureaucracies for the access to users' content. According to Statista (2018), Instagram gains approximately 1 billion active users worldwide every month. The work conducted by Reece and Danforth (2017) needed the help of volunteers to answer a survey and share their data using Amazon's Mechanical Turk (MTurk), word cloud platform, to overcome the limitations of access. At MTurk, registered users get paid to answer surveys of their interest.

The remaining studies were limited to the use online virtual communities little-known worldwide, or of a more public restricted social network, such as the Live Journal Platform,[3] which was used in (Nguyen et al. 2017; Fatima

[3] The Live Journal Platform: `livejournal.com`.

**Fig. 5** Type of information available in the social media and used in the studies




et al. 2017); the Psycho-Babble Grief,[4] used in Karmen et al. (2015); and VKontakte. We,[5] a Russian network used in (Semenov et al. 2015). Live Journal Platform is similar to Reddit, since it has non-specific content. Psycho-Bable is focused on the discussion of psychological problems, providing mutual support, and VKontakte.We is similar to Facebook regarding its supported resources and layout structure.

More generally, Tung and Lu (2016) explored web postings as a whole, such as blogs and sites, and Chomutare (2014) compared postings from a local specific diabetes community. Xu et al. (2013); Cheng et al. (2017) did not specify the social network used in their study.

### 4.3 Social media and techniques employed in the studies

The recognition of mood depressive disorders taking advantage of the analysis of social media content has grown in recent years. Figure 5 shows a summary of the use of social media in the selected primary studies. "Study ID" (represented by the horizontal axis) refers to the number of each study, which corresponds to the ones reported in Table 1. The information types used in the studies and extracted from social media are represented by different symbols, which denote text, log files, images, and emoticons in the analysis.

Text was the only media considered by all studies, except for studies number 5 (Park et al. 2013) and 14 (Reece and Danforth 2017). One of the reasons for this fact is that Twitter is the main social network used, appearing in ten studies, which is mainly based on text information.

In studies 16 (Guangyao Shen 2017) and 20 (Polignano et al. 2017), the authors used emoticons to improve and provide more meaning to the analysis of feelings regarding the text. The work of (Polignano et al. 2017) applied their studies on the Facebook network using NRC Word-Emotion Association Lexicon, WordNet-Affect, as well as Naive Bayes and Multilayer Perceptron classifiers. More recently, Guangyao Shen (2017) proposed a new multimodal depressive dictionary learning model to detect depressed users on Twitter, and compared their solution with Naive Bayes classifier and Multiple Social Networking Learning (MSNL), which was designed by Song et al. (2015).

User log information, i.e., the record of users' activities in the network was used by studies 5 (Park et al. 2013), 7 (Semenov et al. 2015), and 12 (Wee et al. 2017). In the work of Park et al. (2013), the authors used a Facebook Web Application to collect data from a survey with Facebook users, based on the self-report questionnaires CES-D (Steinfield et al. 2007) and BDI (Beck et al. 1961). They also performed a Face-to-Face interview and applied correlation metrics to verify differences between the manifestation of depression reported by users online and personally. Semenov et al. (2015) considered user attributes as age, gender, number of friends, and structural properties of their egocentric networks and conducted a descriptive statistical analysis. Wee et al. (2017) applied quantitative analysis to understand the behavior of users and obtain evidence or indications of depressive behavior. The authors relayed on logging user activity and texts, images, and emoticons. Although all media types were used, no specific algorithm or technique was proposed by them, only quantitative statistical analysis.

As mentioned before, Wee et al. (2017) used images in their work, but only relative to the frequency of the use of images in users' posts, not as an analysis feature. On the other hand, study number 14 (Reece and Danforth 2017) explored the use of only images in the process of detecting depression in Instagram posts. The authors obtained 43,950 photos from Instagram users and used color analysis, metadata components, and algorithmic face detection. The authors used Face detection to recognize a human face in photographs and extracted Hue, Saturation, and Value (HSV) features to find pixel-level averages. Their results show that depressive users' posts had HSV values shifted compared with photos posted by healthy individuals.

Concomitantly to the text, in study 1 (De Choudhury et al. 2013a) analyzed users' log information, while studies number 5 and 7 (Park et al. 2013; Semenov et al. 2015) analyzed users' profiles. De Choudhury et al. (2013a) analyzed users' frequency records in specific activities, including posting frequency, message sending, among others. In (Park et al. 2013; Semenov et al. 2015), the authors analyzed the users' profiles in order to verify demographic features, such as age,

[4] The Psycho-Babble Grief: `dr-bob.org/babble/grief/`.

[5] The Russian network VKontakte.We: `vk.com`.


**(a)** **(b)**

**Fig. 6** Word Cloud representation of **a** the techniques employed in the studies and **b** additional sentiments and mental illnesses recognized in the studies, besides depression

number of joined communities, gender, preferences and user behavior in the network.

The considered studies also employed specific metrics or techniques for each media type. Figure 6a presents a word cloud representation, showing the most cited words in the studies. The most recurrent word is "LIWC", which stands for Linguistic Inquiry and Word Count, a text analysis software that computes the degree of use for different words' categories in a wide variety of texts (Pennebaker et al. 2001). The core of LIWC software is a lexical resource, available in multiple languages such as English and Portuguese (Balage Filho et al. 2013). The high frequency of LIWC mainly occurred because the text was the most used media in the considered studies, and LIWC was used in several studies (De Choudhury et al. 2013a, b; Park and Conway 2017; Nguyen et al. 2017; Fatima et al. 2017). For instance, Guangyao Shen (2017) use LIWC, EMOJI, and the Naïve Bayes classifier to determine the feelings of postings on multiple social networks.

Methodologies for text analysis and processing have also been employed. One example is "SentiStrenth", a polarity verification system used in (Xu et al. 2013), alongside an econometric model. Wang et al. (2013) used several algorithms such as feature extraction methods, Bayesian networks, decision trees and tables of rules. Additionally, in De Choudhury et al. (2013b) they combined the use of LIWC with the lexical analysis package ANEW lexicon (Bradley and Lang 1999) and the Egocentric Social Graph, aimed at verifying activation and dominance. According to the authors, "activation" refers to the physical intensity degree of emotion (for instance, "terrified" is higher in the activation than "scared"). Plus, "dominance" refers to the degree of control in an emotion (for instance, "anger" is dominant, while "fear" is submissive).

Besides the studies focused on the sentiment analysis with LIWC, Nguyen et al. (2017) proposed a regularized regression model called Lasso, and Birjali et al. (2017) applied several traditional machine learning models such as Instance-Based Learning (IBL), Sequential Minimal Optimization (SMO), J48 and CART for classification. Karmen et al. (2015) used the Stanford CoreNLP (Manning et al. 2014) for the lexical sentiment analysis and vocabulary frequency control to implement a grammar-oriented process. Semenov et al. (2015) used a binary logistic regression and a clustering coefficient and Tung and Lu (2016) explored ontology, sentiment analysis, terminology, FAQs, Multiple nominal logistic regression, decision trees, and association rules to determine negative terms. Similarly, Chomutare (2014) used bag-of-words and multiple traditional classifiers, among Naïve Bayes, Support Vector Machine (SVM) and Decision Trees (DT), to find negative terms. Other examples of studies that worked with text are: (Vedula and Parthasarathy 2017), where the authors employed ego-networks metrics; (Leiva and Freire 2017) where the authors used VADER Sentiment Analysis (Hutto and Gilbert 2014; Hassan et al. 2017), which employed Support Vector Machine (SVM), Naïve Bayes (NB) e Maximum Entropy (ME) algorithms.

Park et al. (2013) considered users' profiles and text information, and apply the Spearman correlation and the Mann–Whitney U test by means of IBM SPSS[6] software. In (Wee et al. 2017) the authors used statistic analysis and a Poisson regression method to analyze users' log information.

[6] IBM SPSS: `ibm.com/br-pt/marketplace/spss-statistics/`.

### 4.4 Sentiments, emotions and other explored disorders

The selected studies rely on sentiment analysis and emotion recognition to identify depressive disorders. Thus, each work starts from a specific set of these feelings and emotions, aimed at indicating a depressive disorder. The studies also explore other mental disorders and recognize positive sentiments, mainly to allow the comparison to other techniques. Figure 6b shows a word cloud of the sentiments and mental illnesses recognized in the primary studies, besides depression. It is possible to realize that the feelings and mental illnesses found through the analysis of social media are mostly described as symptoms, specifiers, or predecessors of depression, as described in Sect. 2.

De Choudhury et al. (2013a) found happiness, sadness, and hate as the main emotions, and they were capable of recognizing discomfort, pain, hope, and concern. De Choudhury et al. (2013b) found positive affect (PA), negative affect (NA), activation, and dominance emotions.

Tung and Lu (2016) highlighted anorexia, concentration problems, difficulties of memorization, sleep disorders, anxiety, and suicide-related terms in Web postings. Birjali et al. (2017) found symptoms and traces of anorexia, cyberbullying, fear, heartache, insults, loneliness, and punishment. Wee et al. (2017) found Neuroticism, which consists of a characteristic of emotional instability when a person tends to experience negative emotions such as anxiety, anger, or even depression. Nguyen et al. (2017) found terms that are related to bipolarity disorders, self-mutilation, distress, and suicide.

In works (Xu et al. 2013; Wang et al. 2013; Park et al. 2013; Park and Conway 2017; Reece and Danforth 2017; Guangyao Shen 2017; Leiva and Freire 2017; Hassan et al. 2017; Vedula and Parthasarathy 2017; Seabrook et al. 2018), the authors only considered the polarity of the sentiment or emotion. In (Park et al. 2013; Chomutare 2014; Karmen et al. 2015; Semenov et al. 2015) the authors do not specify sentiments, emotions, and other disorders. Park et al. (2013) had the support of specialists to manually relate the answers of a questionnaire to the questions of the Diagnostic and Statistical Manual of Mental Disorders (DSM-IV) (American Psychiatric Association and others 2013). Chomutare (2014) analyzed only positive and negative affects, activation and dominance, and Karmen et al. (2015) started from the principle of finding the recurrence of synonyms of the word depression in Psycho-Babble postings.

Vedula and Parthasarathy (2017) found a correlation between insomnia and depression. Fatima et al. (2017) found aspects of rejection, frustration, aggravation, as well as being thirsty, scared, listless, lazy, indifferent, sympathetic, touched, surprised, thoughtful, optimistic, and loved. Polignano et al. (2017) recognized the Ekman's universal basic emotions (Ekman 1993) as happiness, anger, sadness, fear, disgust, and surprise. Ophir et al. (2017) analyzed the valence of feelings, but also found anxiety and substance abuse. Lachmar et al. (2017) found dysfunctional thoughts, lifestyle challenges, social struggles, hiding behind a mask, apathy, and sadness, suicidal thoughts, behaviors, and seeking relief. Cheng et al. (2017) recognized suicide risk, anxiety, and stress. Jung et al. (2017) assessed self-harm, anxiety, change of appetite, sleep, hypersomnia, irritability, self-esteem, lowered libido, pain, bullying, stress, personality, academic stresses, and loneliness. Finally, Park and Conway (2018) recognized bipolarity, schizophrenia, loseit, and bodybuilding.

The feelings, emotions, or disorders encountered by the presented studies and shown in Fig. 6b are very similar to those indicated as part of a depressive disorder discussed in Sect. 2.

### 4.5 Identified patterns

Table 2 presents a summary of the different aspects considered in this paper, namely the social networks, media, methods, sentiments, emotions, and other disorders identified in the primary studies. By observing the distribution of items in the aspects being analyzed in this work, we can identify the recurrence of patterns among the studies. Table 3 shows the most frequent patterns.

We identified Twitter as the most employed social network, appearing in ten studies. In all cases, the type of media used was text, and in one of the studies the authors combined text with emoticons. Most efforts employed lexical approaches to explore the information gathered from Twitter. This fact is expected since the information consists of textual data. Also, three of the studies explored Machine Learning (ML) algorithms to analyze the data.

When considering Facebook, the studies used text (four times), image, log information, and emoticon (two times each) as the available media. They explored statistical techniques in two works, mainly for dealing with log information; lexical approaches in other two works for the textual information; and finally, ML approaches in the other three works. The unique effort that employed Instagram, authors considered the images as the media. The three works with Reddit, authors focused only on the textual media, employing lexical and ML approaches to explore the data. Finally, eleven works relied on Live Journal, Blogs/Forum, and other social media in their work. All of them used text, in which one of them also explored Log information combined with text to detect valence. There is no pattern on the methods employed to explore the information of these eleven studies. They counted on a mixture of ML and lexical approaches, ontologies, among others.

The "valence" of sentiments and emotions was the focus of 20 studies. Most of them were based on the analysis of the

**Table 2** Summary of the studies in relation to each aspect analyzed in this work

| ID | Social networks | Media | Methods | Sentiments and emotions | Other disorders |
|---|---|---|---|---|---|
| 1 | Twitter | Text | SVM, LIWC | Valence | – |
| 2 | Other | Text | SentiStrength, Econometric models | Valence | – |
| 3 | Twitter | Text | Man-made rules, feature extraction, Bayesian Networks, J48; Rules Decision Table | Pretty, love, like, happy, good, ugly, sad, depressed, unhappy, bad | |
| 4 | Twitter | Text | Egocentric Social Graph, LIWC, ANEW | Positive and negative affect, activation, dominance | – |
| 5 | Facebook | Image, log | Spearman and Mann–Whitney U test, CES-D and BDI survey | Valence | – |
| 6 | Other | Text | Bag-of-words; Bigrams, NB, SVM, DT | Valence | Distress, disturbed sleep, low self-confidence, poor concentration or indecisiveness, poor or increased appetite, suicidal, agitation, guilt |
| 7 | Other | Log, text | Egocentric networks and binary logistic regression | Valence | – |
| 8 | Blogs / Forum | Text | Stanford CoreNLP | Valence | – |
| 9 | Blogs / Forum | Text | NLP processing, extraction of negative features | Boredom disgust loathing | Memory difficulties, loss of appetite and energy, sluggishness, mental fatigue, overeating, agitation fainting, forgetfulness, anorexia, sleep disorder, irritability |
| 10 | Reddit | Text | LIWC | Valence | Anxiety |
| 11 | Twitter | Text | IBL, SMO, J48 and CART | Valence | |
| 12 | Facebook | Emoticon, image, log, text | User frequency analysis, user activity | Valence | Anguish, emotional instability |
| 13 | LiveJournal | Text | LIWC | Valence | Bipolar disorder, self-harm, grief/bereavement, suicide |
| 14 | Instagram | Image | Image analysis, Bayesian estimation, RF, valencia filter | Valence | – |
| 15 | Other, Twitter | Text | Linguistic Content Analysis, Gradient Boosted Decision Trees | Valence | Insomnia |
| 16 | Twitter | Emoticon, text | LIWC, EMOJI, NB, MSNL | Valence | – |
| 17 | Reddit | Text | Logistic Regression, SVM, KNN, RF | Valence | – |
| 18 | Twitter, Other | Text | SVM, NB, Maximum Entropy | Valence | – |
| 19 | LiveJournal | Text | LIWC, Decision Forests, ANEW | Rejected, frustrated, aggravation, thirsty, scared listless, lazy, indifferent, sympathetic, touched, surprise, thoughtful, optimistic, loved | Anxiety |
| 20 | Facebook | Emoticon, text | NRC Word-Emotion Association Lexicon, WordNet-Affect, NB, MLP | Happiness, anger, sadness, fear, disgust, surprise | – |
| 21 | Facebook | Text | Multiple Regression | Valence | Anxiety, substance abuse |

**Table 2** (continued)

| ID | Social networks | Media | Methods | Sentiments and emotions | Other disorders |
|---|---|---|---|---|---|
| 22 | Twitter | Text | Qualitative content analysis, NCapture | Valence | Dysfunctional thoughts, lifestyle challenges, social struggles, apathy and sadness, suicidal thoughts, seeking relief |
| 23 | Other | Text | Survey, LIWC, Logistic Regression, SVM | Valence | Suicide risk, anxiety, stress |
| 24 | Blogs/ Forum, Other, Twitter | Text | Ontology, sentiment analysis, FAQs, Multiple Nominal Logistic Regression, DT, Association Rules | Anger, sadness, fear | Self-harm, anxiety, change of appetite, hypersomnia, irritability, self-esteem, lowered libido, pain, bullying, stress, academic stresses, loneliness |
| 25 | Facebook, Twitter | Text | LIWC, MoodPrism, Spearman rho, post hoc comparison, Mann–Whitney U tests, SPSS | Valence | – |
| 26 | Reddit | Text | Linear Least Squares Regression, Lexicon diversity | Valence | Bipolar, schizophrenia, loseit, bodybuilding |

**Table 3** Patterns identified in the different aspects considered regarding the primary studies

| Antecedent | Consequent |
|---|---|
| Twitter [10] ⇒ | Text [10] |
| | Text + Emoticon [1] |
| | Lexical approaches [7] |
| | ML approaches [3] |
| Facebook [7] ⇒ | Text [4] |
| | Image [2] |
| | Log [2] |
| | Emoticon [2] |
| | Statistical Approaches [2] |
| | Lexical approaches [2] |
| | ML approaches [3] |
| Instagram [1] ⇒ | Image [1] |
| Reddit [3] ⇒ | Text [3] |
| | Lexical approaches [2] |
| | ML approaches [2] |
| LiveJournal+ Blogs/Forum[11]+ Others ⇒ | Text [11] |
| | Log + Text [1] |
| | Diverse methods (ML, lexical approaches, ontology, etc.) [11] |
| Valence [20] ⇒ | Text [17] |
| | Image [3] |
| | Log [3] |
| | Emoticon [2] |
| | Image + Log [2] |
| | Text + Log [2] |
| | Text + Emoticon [2] |
| | Text + Image + Log + Emoticon [1] |
| LIWC [8] ⇒ | Text [8] |
| | Emoticon + Text [1] |
| | Valence [6] |
| | Twitter [4] |
| | LiveJournal [2] |
| | Facebook + Twitter [1] |
| | Reddit [1] |
| | Other (social media) [1] |

text (17), with image, log information, and emoticon appearing in three other studies. The studies combined image with log, text with log, and text with emotion, two times each. Also, one study combined all available information, text, image, log, and emoticon.

LIWC was the most employed method, appearing in eight studies, in which all of them used text, and one of them combined emoticon with textual information. In six of the studies, the authors focused on detecting valence. LIWC was mainly explored to analyze data from Twitter (four works)

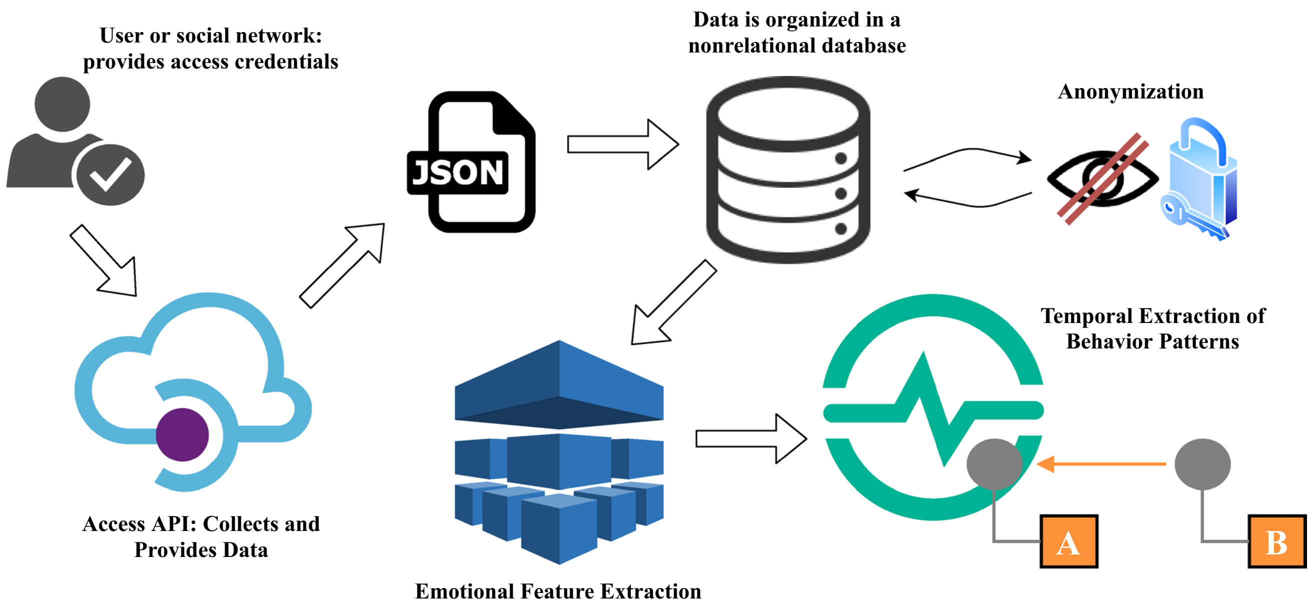



**Fig. 7** High-level pipeline for data acquisition from social networks, data storing and organization, anonymization, feature extraction, and finally, the recognition of depressive behavior patterns considering multi-modality and temporal approaches

and Live Journal (2 works). Facebook and Twitter together, Reddit and other social media were the focus of one study each.

## 5 Challenges and opportunities

The main objective of this work is to present state-of-the-art studies regarding the identification of depressive disorders in social networks. We considered both the analysis of sentiments and emotions. Despite the advances in this field, the selected studies allowed us to identify existing problems and opportunities for research. In particular, we observed the following **limitations**:

1. Most studies focus only on the analysis of textual information from postings, log activities, or demographic characteristics of the users' profile.
2. Most studies did not properly explore the associated media, such as images, videos, and emojis.
3. Most studies did not consider the users' context, i.e. users' history, or look for changes in the users' behavior pattern along time. In fact, the temporal information is often underused.
4. Regarding postings, the studies did not consider the interaction and reactions from user friends in the social networks, like comments and other demonstrations of positivity/negativity.
5. The studies *manually* relate the available information to the Diagnostic and Statistical Manual of Mental Disorders (DSM)(American Psychiatric Association and others 2013).
6. The studies did not provide the computational solution online and did not make it available for testing with other users in real-time.

The aforementioned limitations leave open opportunities for multimodal approaches to identify depressive disorders in social network users automatically. The information regarding long-term user behavior is also relevant, and it was not explored in the studies we selected in this review.

Figure 7 shows a high-level pipeline we envision for future approaches focused on the recognition of depression in social networks. Accordingly, the analysis of the data obtained by particular users along time could lead to accurate results, regarding the users' behavior and the associated temporal information. For instance, it could allow us to take advantage of using frequent patterns mining algorithms to extract relevant information, also relating them to the Diagnostic and Statistical Manual of Mental Disorders (DSM-V) (American Psychiatric Association and others 2013), and allowing real-time analysis.

Given that the gaps pointed out make it challenging to analyze human depressive behavior, the proposed pipeline (Fig. 7) goes from collecting and storing data, through multi-modal extraction of emotional characteristics on social media, to temporal recognition of frequent patterns of depressive behavior.

Another gap that we were able to identify in the state-of-the-art studies is the lack of analysis of the interaction of

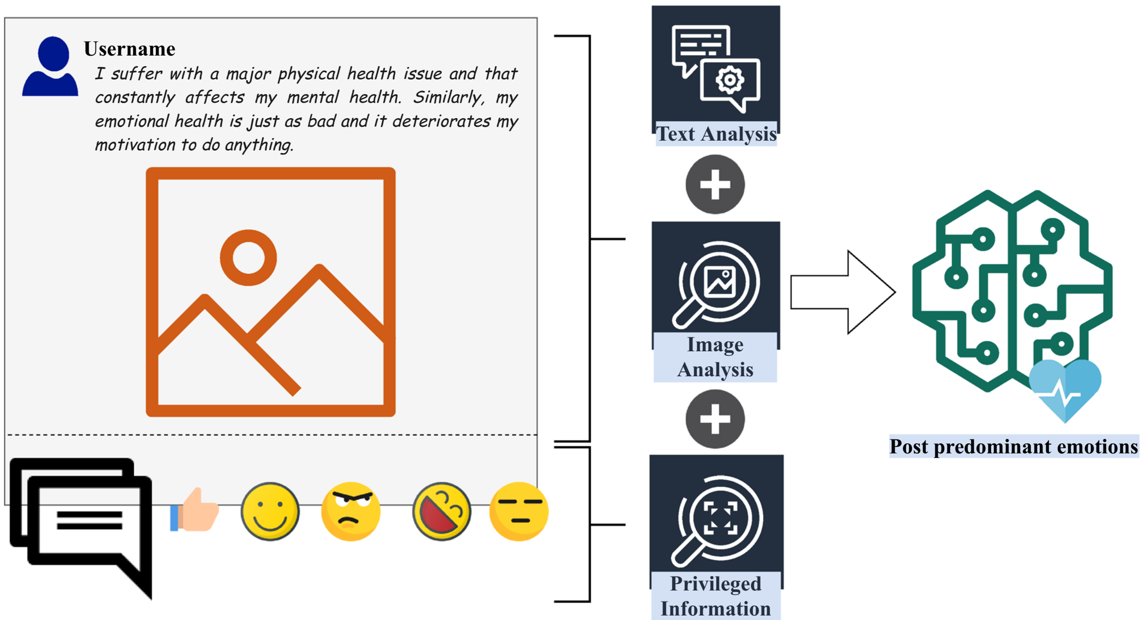



**Fig. 8** Multimodal extraction of predominant emotional features of the post

friends in the social network. The described studies focus on the user data only, without considering the information provided by comments, likes, and other interactions of its connections in the network. Also, we hypothesize that the combination of different types of information, such as text, images, videos, and emoticons, has the potential of improving the overall analysis of the users' behavior. Accordingly, such information could lead to more accurate results regarding the detection of depressive disorders in social networks.

The most popular social networks commonly have an Application Programming Interface (API) for sharing data with applications in various contexts. Examples are Facebook Graph API,[7] Instagram Basic Display,[8] Twitter API[9] and PRAW—Python Reddit API Wrapper.[10] Each network has a different privacy and data sharing policy, but it is usually required to register an application on the platform. Facebook and other branded products (as Instagram) can only collect data with users' permission. The user accesses the external platform, logs in, and decides which data they agree to share. However, in the latest privacy policy, Facebook does not approve applications that are intended for sentiment analysis, making it disadvantageous to the use of Facebook in scientific research. In Twitter and PRAW, the application can access any content but with limited data requests and downloads.

APIs commonly return a single JSON format file. It is interesting to anonymize and store this data in a well-structured way, although this file can be manipulated as the social network returns it. Furthermore, although Generation and Noise Addition techniques are the most widely used to ensure privacy, in our context, we could lose information that is relevant to pattern recognition, given that user context is an important parameter. A straightforward solution would be to replace the unique user identifier (ID) with a unique hash and randomize them. A more sophisticated solution to ensure data privacy would be the use of Blockchain technologies (Zhang et al. 2019). With Blockchain, it is possible to keep track of the researcher who manipulated the data.

In the context of sentiment analysis and multimedia information, the use of a non-relational database such as MongoDB[11] may bring better computational performance, reduce costs due to the use of efficient and staggered architectures rather than a monolithic one. Also, non relacional databases allow developers to execute queries without the need of navigating through the SQL data architecture. Besides that, multimedia recovery can be quick and easy.

After storing and anonymizing the data, emotional features can be extracted. As seen in Fig. 8, a social network post may provide different types of media. A post contains the user identifier (Username) and may contain text, an

[7] https://developers.facebook.com/docs/graph-api.

[8] https://developers.facebook.com/docs/instagram-basic-display-api/.

[9] https://developer.twitter.com/en/docs.

[10] https://praw.readthedocs.io/en/latest/.

[11] https://www.mongodb.com/.

image as well as inside information. In this case, insider information refers to the content that we may or may not have in a post, such as comments or reactions (emoticons). Such insider information can significantly contribute to the process of extracting emotional features, as the user's network of friends can react to the post indicating the polarity, emotion, or feeling involved. An example is the study (Giuntini et al. 2019), which evaluated the expression of basic emotions Ekman (1993) through Facebook reactions. Thus, with the multimedia extraction of the different media involved in each post, and if privileged information is provided, this can be used to ensure the accuracy of the emotional features.

Finally, emotional features can be analyzed over time to extract and evaluate the evolution of frequent behavior patterns. Therefore, approaches such as Association Rules (e.g. Apriori and Fp-Growth algorithms), Classification (Instance-Based Learners (kNN), SVM, Decision Trees and Naïve Bayes), Clustering (e.g., k-Means and Expectation-Maximization (EM) algorithms), Temporal Patterns of Motifs extracted from time series, and temporal patterns (e.g. Allen's Interval Algebra and LSTM) can be explored and combined. However, it is worth noting that the most significant difficulties of exploring temporality in social networks is the fact that there is no regularity in the frequency of users' posts.

Traditionally, mental health professionals have used clinical examination techniques based on information provided by self-report of emotional, behavioral, and cognitive dimensions (e.g., questionnaire, interviews, standard inventories, among others) for the diagnosis and follow-up of their interventions. The thousands of data regularly posted in the social media could be a valuable new source of personal information, that should bring new light to the analysis process.

The evaluation of the available information in big data has shown to be an efficient and effective tool in the study of dimensions of human behavior, particularly for motivational-emotional ones. These data point to the promising direction of the use of social networks as another instrument in the identification process of depressive moods; it could allow quicker and more accurate diagnosis and follow-up.

By working with user-related data, we deal with sensitive information. Provided the proper ethical approval, these new sources of assessment could lead to effective diagnosis and the rapid identification of mood changes. Considering the implications of depression, the efficiency of timely information and consequent decision support for mental health professionals can be a crucial element in the prevention of suicide.

The research roadmap indicates the strengthening of multidisciplinary research, which will hopefully allow, shortly, substantial contributions to health and the computational development of better algorithms. Such efforts will no longer be linked to the analysis of feelings and emotions in social networking posts, which is currently not used in the medical practice, only in virtual environments. The main goal of future works will be the employment of actual recognition of depressive behavior patterns, as well as the identification of social and cultural aspects related to risk factors in a non-virtual environment. In this way, social networks and their media can give special meaning and be used as objects in the area of Psychology. Finally, future studies may further contribute to the construction and evaluation of new public health policies.

## 6 Conclusion

This paper addressed a review of studies on the recognition of depression in social networks. There are techniques that can automatically identify mental health disturbances, considering indicators and symptoms of depressive disorders (American Psychiatric Association and others 2013). We focused on studies that automatically identify abnormal behavioral patterns in social networks. However, their performance is considered sub-optimal. Such studies employ data mining techniques, sentiment analysis, and recognition of emotions approaches. Reliable models are very important since they can eventually provide early detection of depressive mood disorders. This can be the basis to lead to fast interventions by physicians, thus promoting relevant public health solutions.

We investigated the state-of-the-art of studies on the identification of depressive disorders in social networks, considering sentiment and emotion analysis, and observed the following points in the selected studies:

1. The **most employed social media** resources for the **identification of depressive mood disorders** are text, followed by emoticons, log information, and images.
2. The **most employed social networks** for the **identification of depressive mood disorders** are, respectively Twitter, Facebook, Blogs and Forums, Reddit, Live Journal and Instagram.
3. The **most employed techniques** for the **identification and classification of tasks** are classic off-the-shelf classifiers, as Naive Bayes (NB), Decision Trees (DT), Instance-Based Learning (IBL), Multilayer Perceptron (MLP), and Support-Vector Machines (SVM). In many studies, such approaches were combined with lexicons as NRC Word-Emoticon Association Lexicon, WordNet-Affect, Anew, and Linguistic Inquiry and Word Count (LIWC) software was widely employed in the selected studies for text analysis.

The challenges envisioned from this study include analysis of temporal information obtained from specific users over time, the use of different types of information concomitantly, and the combination of analysis techniques with the Diagnostic and Statistical Manual of Mental Disorders (DSM-V), provided by (American Psychiatric Association and others 2013). Finally, we present and discuss a high-level pipeline that systematically organizes approaches and techniques to recognize temporal patterns of depressive behaviors in social networks. This pipeline serves as a guide for future works to explore the main steps related to the detection of depressive behavior in social networks.

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## Compliance with ethical standards

**Ethical Approval** This work has the approval of the Ethics Committee from the School of Arts, Sciences and Humanities (EACH) of the University of São Paulo, Brazil, under register number 88799118.8.0000.5390.

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