A Review of Mental Health Reflection Through Social Media Network

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Abstract

As individuals grow increasingly conscious of the importance of mental health, diagnosing disorders of the mind is becoming an increasingly important issue. Many psychiatrists have difficulty recognising mental illness in people they treat because mental diseases are complicated and can be difficult to diagnose. This makes it thought-provoking to start effective remedy before it's too late. Even while community networking has become a part of daily life for individuals, it has produced a setting where further information is available on a patient's psychological health condition may be accessible. This investigation was performed as a systematic review of the literature (SLR), which is an approach for locating, assessing, and interpreting current resources in order to respond to a series of research concerns. The determination of this research is to address interrogations about text-oriented diagnosis of mental ailments from the online interactions among individuals with illnesses of the mind. The outcomes demonstrate that depression may be identified early on through online activities. because these individuals utilise social media in a way that exhibits specific traits. Because of the limited number of research utilising a character-based method, RNN and other deep learning models are used in research. on the early identification of depression patients, according to this SLR. However, the goal of this research is to discover a technique that will be more successful.

Keywords: Mental health, Systematic Literature Review (SLR), Social Media, Depression, Stress

Introduction

Depression is a prevalent disease that affects a large number of individuals in our modern culture. Parekh defines depression as a medical disease that unpleasantly impacts a individual's way of thinking, feeling, and/or behaving. According to statistics given by the WHO, there were about 322 million instances in the period of 2015, with approximately 788.000 cases ending in suicide 2 (World Health Organization data). Regardless matter how severe a mental illness seems to be, there is still a stigma associated with it in society, where having a mental illness is seen as a mark of weakness and may possibly lead to exclusion from social situations. Rendering to one research, although people recognise depression as a significant problem that requires treatment, they rely that it is less treatable than other mental illnesses. This may lead individuals suffering from mental illnesses to be hesitant to seek professional assistance, resulting in an even smaller number of people being exposed to appropriate therapy. When it comes to battling depression, about 75 percent to 85 percent of those suffering from the condition do not get adequate treatment. 4.

Aside from giving psychiatrists and/or psychologists more information before making decisions, given the current state of affairs in which people often use social media to vent about their problems. Using information obtained from the subject's social media platform, this might potentially result in the likelihood of early discovery which could be used to guide treatment. It is supported by research that indicates students suffering from depressed symptoms use the internet much more than students who do not suffer from the condition. 6. This motivates researchers to develop the most effective technique for early diagnosis of depression 7 8. In order to create a more precise and trustworthy early detection system, this SLR looks for and assesses text-based techniques that may be used for the prompt identification of depressive disorders based on social networking posts.

Methods

The author originally opted on a series of inquiries to investigate something would take action as a roadmap used for the period of this study in order to successfully achieve the aim of this SLR. Given that the goal of this investigation is to deal with the issue in question of "what factors may affect the use of social media as a tool for early identification of depression," the subsequent set of examination queries has been developed:

- **RQ1** – What are the drawbacks of detecting depression using a text-based approach?
- **RQ2** – Which text-based methods are best for identifying early signs of depression in children?

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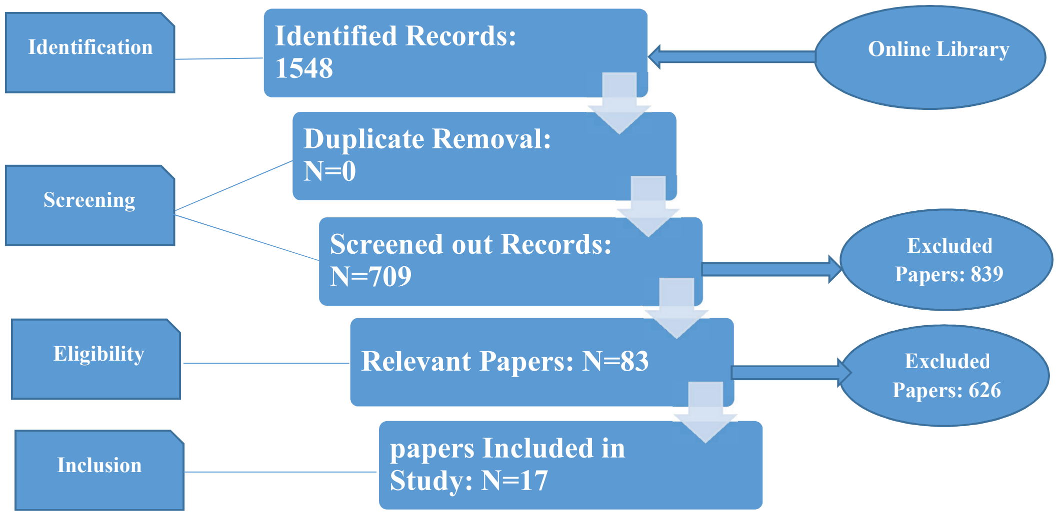
Figure-1



Source: Created by author

To ensure that the whole procedure and the records used in this study are appropriately documented and organised, the PRISMA framework will be used as the primary framework for the current literature review. Figure 1 depicts the steps taken throughout this investigation.

Articles utilised in this research were found by searching several electronic databases, including websites such as Direct Science (www.sciencedirect.com), The dl.acm.org, International Educational Exchange Explore Online Library (ieeexplore.ieee.org), Springer Link (link.springer.com), and Emerald Insight (www.emeraldinsight.com) (www.emeraldinsight.com). After constructing a base search query among these libraries that includes terms like [“depression” or “depressed,”] [,”mental*.” or “disorder,”], [,”detection,”] and [“social media,”], By amending the query to correspond with each platform’s supported format, an assortment of records can be identified and processed further in the next phase. Information that are not research publications published in English will be eliminated from inclusion during this step of the process, which involves further screening the collection of records using a number of criteria. Additional elements that might exclude a search result from being featured in this evaluation are:

- Articles Published Prior to the year 2015;
- Articles Published twice in the same journal;
- Other depression-related problems not addressed in the search results

In the subsequent stage, abstract screening will be used to further select manuscripts that don’t fit any of the requirements for exclusion which will be performed after the first level. Separately record’s complete manuscript will be tested first, and if it is available, the writer will look through its abstract to determine whether or not the contents of the document in contextual is in line with the goal of this investigation, and whether the data might potentially answer the predefined study inquiry. If a record meets both of the previously mentioned requirements, it will be considered for insertion in this review. Table 1 shows the specifics of the outcome obtained throughout the procedure of document looking up.

Table-1: Selected Records

Source	Found	Sample	Selected
Science Direct	449	35	6
IEEE	1	0	-
ACM Digital Library	181	24	6
Emerald	146	3	-
Springer	771	21	5
Total	1548	83	15

Source: compiled by author

Results

A List of Papers that have been published

A total of 17 research publications have been selected for additional analysis in this study based on the information displayed in Table 1.

Table 2 indicates that there are 17 publications in all.

Table 2. List of Paper Publications

Source	Year	Title
Science Direct	2015	Detecting Suicidality on Twitter
Science Direct	2017	Psychiatric Symptom Recognition Without Labeled Data Using Distributional Representations of Phrases and on-line Knowledge
Science Direct	2018	A Large-Scale Social Media Corpus for the Detection of Youth Depression
Science Direct	2018	An Automated Psychometric Analyzer based on Sentiment Analysis and Emotion Recognition for Healthcare
Science Direct	2019	Detecting Arabic Depressed Users from Twitter Data
Science Direct	2020	Predicting Anxiety, Depression and Stress in Modern Life using Machine Learning Algorithms
ACM Digital Library	2018	Beyond the Coded Gaze: Analyzing Expression of Mental Health Illness on Instagram
ACM Digital Library	2018	Individual Informatics in Social Contexts: Towards Technology Design that Facilitates the Social Ecologies of Long-Term Mental Health Care
ACM Digital Library	2019	Exploring Indicators of Digital Self-Harm with Eating Disorder Patients: A Case Study
ACM Digital Library	2019	Leveraging Routing Behavior and Contextually-Filtered Features for Depression Detection among College Students
ACM Digital	2019	Prediction of Mood Instability with Passive Sensing
ACM Digital Library	2018	Interpersonal Contexts for Personal Informatics: In the direction of creating technological solutions that enhance the social environments of long-term mental health care
ACM Digital Library	2019	Who is the “Human” in Human-Centered Machine Learning: The Case of Predicting Mental Health from Social Media
Springer Link	2015	Teenager’s Stress Detection Based on Time-Sensitive Micro-blog Comment/Response Actions
Springer Link	2016	A Systematic Exploration of the Micro-blog Feature Space for Teens Stress Detection
Springer Link	2017	Latent Sentiment Topic Modelling and Nonparametric Discovery of Online Mental Health-related Communities
Springer Link	2020	Recognising Depression Through Psycholinguistic Patterns in Texts on Social Media
Springer Link	2020	Using Temporal Psycholinguistic Cues to Estimate Suicidal Intent

3.2 The Findings of Different Studies

After completing the portion of the study, the writer will review all record in turn then make an effort to get information from each one that was mentioned in Table 2. Gathering of data is carried out in order to respond to the pre-set research questions (RQ) mentioned in the first section of chapter 2.

When developing a text-based method for depression diagnosis, what are the difficulties you face?

Table 3. Challenges with text-based depression identification

No	Issue	Number of papers	Study identifiers
1	Nothing to confirm the accuracy of the data	1	10
2	Dataset is not able to provide significant features.	2	10, 19
3	Ethical concerns	6	10, 16, 17, 18, 20, 21
4	Incomplete data	4	11, 12, 18, 19
5	Stigma and/or lack of awareness	3	14, 20, 21
6	Error intensity	2	16, 17
7	Excessive simplification	1	21

Table 3 displays the level of difficulty indicated in the records that were chosen. Despite the fact that not every article mentioned a problem that occurred during the study procedure, it demonstrates that the majority of concerns are centred on ethical issues. This includes every aspect of data security and accessibility, as well as privacy protection. Information on mental health and disorders is deemed sensitive, even though the majority of the data is published publicly on social networking sites.

Following additional investigation, it seems that the majority of the problems listed in Table 3 are linked to one another in some way. For example, record number 10 said that owing to ethical issues, it is impossible to determine whether or not the Twitter user is really suffering from depression in this instance. As a result, data collection is accomplished via the use of APIs, which may result in a poor sample characteristic and/or data dispersion.

3.2.2. Which text-based technique is best for identifying depression at an early stage of the illness?

Table 4. Techniques for text-based identification of depression

No	Method	Study identifiers
1	Scikit-Learn Toolkit machine classification	10
2	Classifiers	11, 14, 19, 23
3	Support Vector Machine	13, 14, 15, 22
4	Unsystematic Forest	14, 15
5	Probabilistic classifier	14, 15, 22, 24
6	Grouping Approach	15, 24
7	Association rule mining	19
8	Logistic	22
9	Gaussian Process	22
10	Time Frequency – Reverse Document Frequency	25
11	BiLSTM + Attention	26

Table 4 lists the techniques that were utilised in the text-based approach for depression identification that were investigated. While classifiers, support vector machines (SVM), and probabilistic approaches (Bayesian, Hierarchical Dirichlet Process, and so on) are the most common techniques employed in the set of chosen articles, the best results are achieved by combining BiLSTM and Attention model. However, because of the differences in the datasets used and the differences in the issues addressed, this may be an overgeneralization.

Experiment

According to the findings of the literature study, the BiLSTM + Attention model works well on textual material that is linked to depressive disorders. Even if the outcome of the research may have been acceptable, there are some concerns about the model that was used in the study.

They suffer from an issue known as Recurrent Neural Network Model (RNN) based model, where they have difficulty in determining the appropriate context of a word in a lengthy phrase. This is due to the nature of RNNs, which analyse data in accordance with the order of words in a sequence, which causes this. Aside from making it more difficult to discover context, the nature of RNN makes it more time-consuming to train the model.

Another problem with this model is the manner in which it approaches a series of actions. Contrary to its name, BiLSTM really outfits a sequence processing model that courses a arrangement in both ways, thereby rendering this ideal to be not truly bidirectional but rather asymmetrical. Since a result of the fact that it approaches a text from both directions because there is probably more information available, it gets more harder for this algorithm to detect the context of a word. This encourages the author to carry out an experiment utilising a model based on the BERT model to significantly increase the model's accuracy. It has been demonstrated that BERT not only operates faster, but it also solves the two aforementioned issues. However, the conducted experiment will not be repeated; rather, it will only be used as a preliminary experiment to confirm the outcomes of this literature study.

This research utilised a BERT-based classification ideal that has previously been pre-trained by Google 27 for categorization. The model is intended to support transfer learning, it was put through a pre-training process that involved using the English Wikipedia and BookCorpus to help the model learn the language. The model is now ready to facilitate transfer learning. Because this training procedure consumes a significant amount of resources and time, a pre-trained model can be more effectively adjusted for a specific downstream application. An example dataset scraped from Reddit 28 will be used to fine-tune the model's performance in terms of depression detection in this experiment.

The fact that BERT is built by piling encoders on top of one another suggests that it has a self-attention layer. Self-attention layers speed up training and enhance model performance, but at the cost of restricting the model's ability to interpret sequences longer than 512 tokens. The most optimal solution to this problem is found to be to reduce the sequence to the necessary length of 29 characters, or less. However, it is possible that some important information may be lost as a result of this. This experiment will use extractive summarization to longer sequences than the last experiment, which is a fresh method. To alter the sequence's duration, use more than 512 tokens. The unprocessed data and the outcome that was produced by combining it and the summary result are both displayed in Table 5 to illustrate the summarization outcome.

Table 5. Both unprocessed and condensed data

Before	I need to change my depression medication, but I'm terrified. Celexa 40mg has been a part of my life for more than 18 years. The current situation is untenable; something must be done; yet I'm terrified that things will become much worse!! My doctor prescribed me Prozac for a month, but I didn't take it because I was afraid. Earlier last month, he gave me a new medication called Trintellix, which I haven't taken yet. I'm so close to losing my mind that I'm afraid to try anything new for fear that it won't work (or, God forbid, makes me worse...), and then I'll know for sure that I won't make it. What should I do in this situation? Is there anybody else who has been too afraid to attempt new or different medications??
After	I'm so close to losing my mind that I'm afraid to try anything new for fear that it won't work (or, God forbid, makes me worse.....) and then I'll know for certain that I won't make it through.

For the purpose of summary, this experiment chose the extractive approach over the abstractive way in order to preserve as much information as possible without changing any element of the sequence. BERT-for-extractive-summarization 30 is a BERT-based model that use BERT's text embedding before passing it through the K-Means method to cluster the embeddings, resulting in an extractive summarised sequence. It is necessary to configure the text summarization such that it has a ratio of 0.2, a minimum length of 20 typescripts, and a maximum length of 500 typescripts in order to do data preparation. The exemplary will initially reduce the records to 20% of its original underdone form before eliminating any orders that are less than 20 characters and lengthier than 500 characters.

As previously mentioned, the model is then fine-tuned by post-training it on the pre-processed data, which comprises of 3412 data points, with 1884 figures points categorised as disheartened and the supplementary 1528 data points characterized as controller, as described before. A learning rate of 2x10-5 is used in conjunction with an epsilon of 1x10-8, and the process is repeated until 4 epochs have been reached with a batch size of 8, after which it is assessed using a train-test split of 90 percent to 10%. After then, another ten percent of the training set is isolated to serve as the validation set, which helps to prevent the model from being overfit. The model, as exposed in Figure 2, attains a preparation accuracy of 99 percent and a justification accurateness of 92 percent on the fourth part epoch; however, as shown in Figure 3the validation loss on the fourth epoch was 0.40, whereas the training procedure had a loss value of 0.02. The model has to be fine-tuned for a total of 20 minutes, or around 5 minutes every epoch. The model produces a satisfactory result when evaluated on the test set, but it is believed that the summarization configuration has an impact on some element of the model; as a consequence, it is essential to identify the optimum configuration for performance optimization.

Conclusion

This SLR examines the present operation of a written method for early sadness diagnosis, which is being used to identify the condition. Following a search of online databases, the study began with 1548 records obtained, this, following additional exclusion based on a set of criteria, was reduced to 709 articles. These were then further clarified by label and abstract to produce 17 comprised articles, every one of whose materials would be looked at in order to address the research topic that this study aims to address.

The results comprehensive evaluation of the literature indicate that the three utmost concerning subjects are (1) data scarcity, (2) moral concerns, and (3) stigma and/or ignorance regarding mental health.. This research also provided an overview of the techniques presently in use for text-based depression identification that are currently available. It is noteworthy that the BiLSTM + Attention technique, despite the fact that it has been stated that (1) Classifiers, (2) Support Vector Machine, and (3) Probabilistic Classifier are the most common approaches, is the one that produces the greatest results, according to this study.

Taking a BERT-based model and fine-tuning it for depression detection, this research also suggests a novel approach for dealing with lengthy sequences by summarising the text before feeding it into the model, which was used in this work as an experiment. Current results outperform any text-based depression detection model, but future improvement of the performance of this model will need additional optimization, such as summarizer setup or hyper-parameter tweaking.

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