International Journal of Research in Engineering and Applied Sciences (IJREAS)
Available online at http://euroasiapub.org/journals.php
Vol. 10 Issue 03, March - 2020
ISSN(O): 2249-3905, ISSN(P) : 2349-6525 | Impact Factor: 6.573 | Thomson Reuters ID: L-5236-2019

Revisiting Depression Detection Paradigms Using Machine Learning Approaches

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Abstract

People often post numerous things on online media while expressing their feelings. Analysing the shared posts is often useful in detecting depression at an early stage. Early detection of undiagnosed mental illness may even assist towards life-saving activities. Our paper provides an exhaustive review of the existing methodologies dedicated to the task of detecting depression in texts posted on an online forum. Considering the carried-out researches, separation of researches is directed in this paper along with detailed description related to the contributions to the work. This study has concluded that depression detection in online forum can even be extended by incorporating more influential factors that may provide some light to the future direction of this work.

Keywords: Depression Detection, Predictive tool, Social Media, Sentiment Analysis, Shared posts.

INTRODUCTION

The arrival of social media has enabled people to connect with each other and provided them with a platform for expressing their opinions, thoughts, and emotions openly. Social Networking sites like Facebook (Mazman and Usluel), Instagram (Sheldon and Bryant), Reddit (Arumae et al.), Orkut (Spertus et al.), Twitter (Kateb and Kalita), LinkedIn (Skeels and Grudin), etc. have offered a deep and personal insight into the day to day activities of its users, providing valuable information about their lifestyle and preferences.

The widespread use of social media may provide opportunities to help reduce undiagnosed mental illness. By analysing the various user posts and interaction activities, it is possible to observe user sentiments, including signs of depression. This diagnosis can help prevent certain users from taking the extreme step, thereby benefitting society as a whole. Depression continues to be underdiagnosed with most of the cases being detected by physicians (Cepoiu et al.), with only 13-19% of them receiving adequate treatment (Wang et al.). This analysis of social media (Scott and Carrington) allows for development of methods for the early detection of depression in users. If the developed method could detect abnormal depression scores in a user early on, then they could be targeted for proper assessment, exhaustive clinical treatment, and support. It is important to note that all the methods discussed in this paper consider online social media for depression detection. However, persons who are not approachable or not expressive to social media cannot be identified as depressed using these methodologies. Although the rates of correctly diagnosing depression have improved considerably over time, a good percentage of cases go undetected. People's tendency to hide any issues related to the mind, makes depression detection and diagnosis an extremely difficult task. Social Media has provided people with an open platform to express themselves freely. Symptoms related to mental illness have been observed on user posts online. Automated detection methods can be applied to identify depressed and at-risk individuals. This would enable us to provide them with the much-needed help in private, thereby encouraging users to talk and be more open about their problems.

Automated Social Media Analysis (Scott and Carrington) is generally accomplished by building predictive models. These models take in "features" – variables extracted from the data available on social media online – as input, study them thoroughly, and then use them to make predictions. Commonly used features include user post time, users' language encoded as frequencies of each word, self-references, cognitive words and other variables. Machine learning (Michie) approaches take these features as independent variables, and use them to make predictions. Predictive algorithms are trained on a part of the data (the training set), and then tested on the remaining part (test set). Applying these algorithms attain to detect depression level expressed in social media.

In our paper, we present a deep and insightful study of the various ways of detecting depression in users by analyzing their social media post. Section II briefly discusses the existing depression detection methodologies. These methodologies have been divided into three categories based on their techniques: Statistical approaches (Aitchison), machine learning approaches (Michie) and multi-modal approaches (Ngiam et al.). Finally, the paper is concluded in Section III by discussing the future work possible in this field.

Literature Survey

This section provides a thorough discussion of numerous studies carried out in automated depression detection schemes. Methodologies implemented in this domain can be categorized into three sections: Statistical Approaches (Aitchison), Machine Learning Approaches (Michie) and Multimodal approaches (Ngiam et al.).

A- Statistical Approaches

In this section, those researches have been included that were carried out by implementing statistical analysis. Tweets were examined using several Natural Language Processing (NLP) (Manning et al.) techniques. The resulting feature-vectors were then utilized as input for analysis using statistical techniques (Aitchison).

De Choudhury et. al. in (De Choudhury, Counts, and Horvitz) employs crowdsourcing technique to collect data of those Twitter users who have reported of being diagnosed with clinical depression, based on standard tests that have been conducted on them by their respective doctors. The assimilated data comprises of the user's social media posts one year prior to being diagnosed with depression. The collected data is then studied exhaustively to discover the signs of depression by measuring user interaction, development of his/her egocentric graph, predicting the emotional state of the user, measuring the linguistic style of the user using LIWC (Pennebaker et al.), and defining specialized features for characterizing the language used by the people who have depression. Using these behavioural signals, a statistical classifier has been built to guess whether the person has depression or not. De Choudhury et. al. (De Choudhury, Counts, and Horvitz) find that social media contains useful signals such as decrease in social activity, raised negative affect, highly clustered ego-networks, heightened relational and medicinal concerns, and greater expression of religious involvement can be used to describe the start of depression in individuals. The idea discussed in this paper can be used to develop an online depression signal detector which can raise red flags the moment it discovers users displaying the signs of depression. This provides the users with the appropriate help before the onset of severe clinical depression.

Postpartum depression is detected in (De Choudhury, Counts, Horvitz, et al.) by surveying alongside a PHQ-9 (Patient Health Questionnaire) depression screening on mothers who use Facebook and had given birth within the last nine months or less. The study collected demographic information, primary information of the child along with the history of mental illness and the birthing experience, and hence, constructed a confusion matrix based on self and PHQ-9 reported (PPD), correlating premature childbirth and more than one births to it. Several statistical models were constructed to predict PPD, but the demographic model with linguistic style exhibited maximum performance. It is important for the model to expand its dataset and to be able to measure the severity of depression, as it might escalate to psychosis.

Sho Tsugawa et. al. (Tsugawa et al.) investigated the effectiveness of using users' social media activities for estimating the degree of depression. The results of web-based questionnaire are used for measuring Twitter users' degree of depression. Several features are extracted from the activity histories of Twitter users. These features were – word frequencies, ratio of tweet topics, ratio of positive and negative affect words, no. of tweets posted per hour and per day, etc. The results obtained from the experiment are explained as follows-

- Features obtained from user activities can be used to predict depression of users with an accuracy of 69%.
- Topics of tweets estimated with a topic model are useful features.
- Approximately 2 months of observation data are necessary for recognizing depression.

The outcome of the result predicts the posting frequency was the highest at 11 pm and the lowest at 4 am through 5 am among all the participants.

B-Machine Learning Approaches

This section elaborates detailed analysis of machine learning approaches (Michie) applied on social media data. Collected data are analysed using ML techniques (Michie) accompanied with NLP (Manning et al.) techniques. Some researches were also carried out using Deep learning (DL) (Schmidhuber) methodologies. DL techniques are subset of ML techniques which are capable enough of providing promising results in this depression detection field. Description of the approaches along with the techniques, datasets are provided as follows-

A total of 28,749 non-clinical Facebook users and their status updates having at least 500 words are studied in (Schwartz et al.) for predicting and characterizing their degree of depression (DDep). The prediction has undergone through identifying four divisions such as n-grams, topics, lexical and number of words. The dataset comprised of two subsets; testing samples with 1000 random users who wrote a minimum of 1000 words and training set containing the rest. The test was conducted on all messages and the messages written in the same three months as the survey administration to ensure consistency, and a cloud was built containing a glossary of most frequently used words by depressed users. The model allowed for seasonal change in depression; showing a peak during winter, and did best when trained with the National Research Council (NRC) sentiment feature and then applied to all messages in the test set. However, by adding more information into the dataset and accounting for non-textual data, the model performance may be improved.

The performance of four classification techniques –Naïve Bayes (Zhang), K-Nearest Neighbors (Keller and Gray), Decision Trees (Quinlan J.R) and Support Vector machines (X. Huang et al.), for detecting depression in short texts written by users in online forum is compared in (Kateb and Kalita). This paper finds it relatively easy to deal with short texts, as opposed to long texts, since the former vastly improves the efficiency of the feature extraction stage. This research (Kateb and Kalita) also discusses the challenges of streaming textual data.

According to WHO, suicide is the second leading cause of death for women age 15-19. Suicidal tendency estimation is focused in (Coppersmith et al.). The objective of (Coppersmith et al.) is to examine data from the Twitter users who have attempted to take their life and provide an exploratory analysis of patterns in language emotions around the attempt. The tweets of those people who attempted suicide, was analysed in (Coppersmith et al.). The n-gram language model was used to extract features from those tweets. Logistic Regression was then used to perform the classification. The carried-out work has the following contributions-

- To find out the quantified signals of suicide.
- To provide an intuition about the data via simple visualization of linguistic content.
- To uncover interesting patterns in the emotional composition of posts by users in the time around a suicide attempt.

This simple analysis can provide a foundation for non-invasive screening and interventions to prevent suicides.

Machine learning and natural language processing for sentiment analysis techniques are approached in (Xiaohui Tao(B), Xujuan Zhou, Ji Zhang) in order to estimate how a social media including Twitter can be used to detect and determine depression. The "Sentiment Analysis for Depression" tool was developed which will first collect data that consists of contributors' depressive words. Collected data will be analysed by Depressive Sentiment Vocabulary. Two different parts will be there. The 1st one will be demonstrated by using laptop and second one by using mobile phone. The contributions include a depressive sentiment knowledge base and an algorithm to analyse textual data for depression detection. Such an approach offers social workers the ability to access potential depression at an early stage.

In (Deshpande and Rao), emphasis has been given on Twitter data while detecting depression using emotion analysis. A total of 10,000 records are collected from Twitter API and has undergone through tokenization, stemming stop words removal, POS tagging. This will produce a pre-processed data which in turn helps to generate a Bag-of-Words (Wallach) model. This model will be utilised as feature for support vector machine (SVM) (X. Huang et al.) and Naive-Bayes (Zhang) classifier for training and testing purpose. Experimental result has shown that Naïve Bayes (Zhang) classifier performs better than SVM (X. Huang et al.). However, applying other supervised learning algorithms may improve the performance of this depression detection tool.

A semi-supervised two-approach based depression detection technique is implemented in this paper (Yazdavar et al.) that considers nine syndromes of depression. A statistical model is approached in this paper that assimilates lexicon-based technique with a semi-supervised topic modelling technique. The first approach follows a bottom-up approach that captures clinical depression on user tweets and detects depression symptoms based on related word clusters. This approach exploits the concept of Latent Dirichlet Allocation (LDA) (Blei et al.) that identifies the frequency of the co-occurrence of terms in several contexts. The second approach utilises top-down processing that uses lexicon terms for perceiving the extraction of symptoms from tweets.

Sadeque et al. in (Sadeque et al.) focus on obtaining an automated tool that detects depression in users by studying their posts on Reddit (Arumae et al.). A comparative analysis is drawn among the working of the SVM model, RNN model and an ensemble model. Five early risk detection models presented in (Sadeque et al.) are discussed as follows:

- UArizonaA: An SVM (X. Huang et al.) model trained using LibSVM (Chang and Lin), which employs Metamap outputs and depression lexicon as features.
- UArizonaB: An SVM (X. Huang et al.) model using WEKA (Hall et al.) with depression lexicons as features.
- UArizonaC: An RNN (Tom) model which uses Metamap outputs and depression lexicon as features.
- UArizonaD: An ensemble method.
- UArizonaE: An RNN (Tom) model with the same structure as UArizonaC, but that always predicts “wait” until 60% of the test data is released.

Experimental analysis concludes that UArizonaD is superior since the highest F1 score with the second-best recall is obtained from this model.

A research in (Stankevich et al.) was carried out to detect depression in Reddit (Arumae et al.) users by analyzing their text messages. In this context, a varying number of text messages were reviewed over a period, based on the frequency of words used and an average of the word embeddings. Furthermore, n-grams were used for language modelling, authorship attribution, sentiment analysis, etc. It concluded that additional features such as stylometry and morphology improved the overall classification result. Although tf-idf headed with the best accuracy and precision; assembling it with morphology achieved the best F1 scores. The major drawback that presents itself here is the lack of generalization and the inability to assess multilingual texts.

The objective of this paper (Alhanai et al.) was to diagnose a subject with depression, with outcomes stating the binary state and severity of the subject's depression. Scores ranging from 0 to 27 were utilized, with a soft cutoff between 12 and 17 for the binary outcome. The subjects were assessed with unconditioned as well as type-conditioned but time-independent queries. Along with this, temporal changes in audio and text were also studied to determine depressive characteristics of individuals. Long short-term memory (LSTM) (Z. Huang et al.) neural network's multi-modal model revealed that the combination of two modalities increased the discriminative power along with additional complementary information. The model could be farther calibrated to achieve lower Mean absolute error (MAE) (Alhanai et al.) and Root mean-square error (RMSE) (Alhanai et al.) performance.

Kantinee Katchapakirin et. al. (Katchapakirin et al.) put their concentration on depression perceived on Thai people. According to statistics, around 1.5 million Thai people suffer from depression and its prevalence has been growing up fast. The objective of this paper is to determine depression using Facebook since it is the most popular social network platform in Thailand which may serve as an extensive resource for depression detection tool. Natural Language Processing (NLP) (Manning et al.) techniques are accompanied with Support Vector Machine (SVM) (X. Huang et al.) algorithm, Random Forest (Ham et al.) algorithm, and Deep Learning (Schmidhuber) algorithms which are applied on Thai language on Facebook (Mazman and Usluel). The predictive tool successfully predicted depression level for 35 Facebook users with their shown behaviour.

Depression is a common mental illness so depression detection is a significant issue for human well-being. The objective of this paper (T. Shen et al.) is to focus on the possibility of enhancing depression detection via social media including Twitter (Kateb and Kalita) and Weibo with multi-source datasets. At 1st, the researchers systematically analyse the depression related feature patterns across domains and summarize two major detection challenges isomerism and divergence. A cross domain Deep Neural Network model with Feature Adaptive Transformation and Combination strategy (DNN-FATC) was developed to transfer relevant information across heterogeneous domains. Based on the Twitter and Weibo datasets, certain experiments are performed such as Min-Max Normalization (MN), Zero-mean Normalization (ZN), Feature Normalization and Alignment (FNA), Direct Learning (DL), Direct Transfer (DT), Divergent Feature Convertion (DFC). Experiments demonstrate improved performance compared to existing heterogeneous transfer method.

Orabi et al. in their paper utilises the best deep neural network architecture for recognizing users showing signs of mental illness. A novel word-embedding approach is approached in (Shin et al.) for identifying users suffering from depression by analysing their tweets and other social posts. Depression detection is performed on two datasets – CLPsych2015 and Bell Lets Talk dataset. Four deep learning models such as CNN (Shin et al.) With Maxpooling, Multi-Channel CNN (Shin et al.), Multi-Channel CNN (Shin et al.) with Multi-Maxpooling, and a Bidirectional LSTM (Z. Huang et al.) with attention are compared and analysed. The optimized CNN (Shin et al.) with Maxpooling model shows the best performance on the CLPsych2015 dataset, whereas the optimized Multi-Channel CNN (Shin et al.) shows the best accuracy on the Bell Let's Talk dataset. Incorporating other Deep Learning models such as RNN based models can improve the analysis process.

Gaikar et.al in their paper (Gaikar et al.), introduces a technique that not only detects signs of depression in tweets but also advances to categorize them as either Bipolar or Major. The paper discusses the use of a Hybrid Model that combines the simplicity of NB (Zhang) classifier along with the accuracy of SVM (X. Huang et al.) classifier. After the pre-processing stage, which involves lemmatization, change of case, and the removal of stop words, the system then tries to extract features from the pre-processed text. Here the system only focuses upon the adjectives (unigram) (Beigman Klebanov et al.), since they are the words that people mostly use to describe things happening in their lives or the world outside. This paper uses NB (Zhang) as a vectorizer and SVM (X. Huang et al.) as a classifier.

C -Multi-Modal Approaches

This section provides a detailed analysis of depression detection techniques that use the multi-modal approach. This approach combines multiple techniques that use different modalities. The use of multimodal techniques may result in a significant increase the effectiveness of system.

The objective of (G. Shen et al.) was to detect depression in individuals based on their twitter posts. The categorisation was done based on the anchor tweet '(I'm/ I was/ I am/ I've been) diagnosed with depression' and consequently three datasets were designed, depression dataset D1, non-depression dataset D2 and dataset D3 that included tweets loosely hinting at depression. For manageability, emojis, typographical mistakes, abbreviations as well as the tense and voice of the text, were overlooked. Six features such as social network, user profile, visual, emotional, topic-level and domain-specific were set up. It was concluded that the multimodal and lexicon learning strategy was effective with emotional modality contributing significantly to the result.

Zucco et al in (Zucco et al.) study the applications of sentiment analysis and affective computing for identifying signs of depression in users. A multi-modal approach is proposed in (Zucco et al.) where sentiment analysis and affective computing methods are combined in order to detect depression in users by studying their social media posts. The paper proposes three types of fusion: feature-level fusion, matching score level fusion, and decision level fusion. The authors wish to test the three solutions and evaluate their performances. The model can be extended to deal with facial expressions and change in tone while communicating with other people which provides insight to future work of this paper.

This section has provided an extensive study regarding the carried-out researches on the field of depression detection. However, the study is limited to analysing emotions in social media. Depression detection in social media often dependent on individuals since many introvert people do not prefer to use social media. Hence, their depression may be not be detected using the aforementioned explained techniques.

CONCLUSION AND FUTURE WORK

Detailed review process pursued in this paper advocate for more emphasis to be placed on using social media to identify users showing signs of depression and mental illness. Advances in the field of Natural Language Processing and Machine Learning have warranted for an increased emphasis on large-scale screening of social media for not only depressed individuals, but also recognizing the onset of mental illness.

Based on the understanding of the studies pursued in depression detection field, following directions are provided which may be carried out for obtaining more fine-grained predictive tool.

1. Incorporating all Social Media Accounts:

Since, social media data are considered which analysing mental state of a specified user, incorporating all possible social media account data may help in diagnosing more accurate depression detection. While implementing the above-mentioned factor, big data based distributive approach can be incorporated as proposed framework. This mechanism may incorporate several social media accounts such as Facebook, Twitter, Instagram, WhatsApp and many more. While analysing all possible social media accounts, the platform where people more share their feelings towards any incident can be identified. Identifying this impactful social media will definitely help in preventing outcomes of depression. Considering and analysing non-textual data such as shared pictures, videos, audios may assist in obtaining more accurate depression level.

2. Deep-Learning Models:

Several researches such as (Alhanai et al.) (Shin et al.) have been carried out based on deep learning methodologies. Expanding the frameworks by incorporating more RNN models and/or combined RNN models may help in more detailed analysis. Applying NLP techniques along with RNN models will assist in obtaining accurate depression detection tool.

Implementing the above-mentioned directions under a single platform will yield depression detection tool in order to achieve maximised efficiency. This idea may be extended while designing a depression detection model that offers medical advice along with depression detection. In this context, legal ramifications need to be considered as well.

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