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A Systematic Review of Machine Learning Classification Approach for Suicide Ideation Detection

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ABSTRACTS

Suicide is a global health issue that is responsible for several deaths among young children and adults. Suicide can easily be handled if it is detected early. To address this issue several approaches have been used, which are clinical method and machine learning with feature engineering or deep learning for automatic detection of suicide ideation based on an individual social media messages. This paper aims to survey different methods used for suicide ideation detection. Some of the domains of machine learning applications used for suicide ideation detection were also reviewed based on their data sources like questionnaires, electronic health records suicide notes, and online user contents. Several specific tasks and datasets are introduced and summarized to facilitate further research. Finally, this paper summarizes the limitations of current work and provide an outlook for further research directions.

Keywords: Systematic Review, Machine Learning, Classification, Suicide Ideation Detection

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1. BACKGROUND OF THE STUDY

There is an extensive literature on suicide risk assessment, management, prediction and treatment for young adults between the undergraduate ages range of 18-29. Suicide risk assessment has been on the forefront of most literature as most mental health professionals are of the view that mental health is predominantly the only cause of suicide. While most researchers believe on this some others believe that some environmental factors (such as sexual abuse, trauma, economic problems, academic stress, etc) can trigger these mental problems and make an individual susceptible to suicide. Most literature are of the view that the first point of call for every suicidal case is to assess suicide risk factors in individuals and based on that predict those who might develop suicide ideation. While these works in some cases, it fails in others as some people have taken their lives months after contact with mental health professionals (Carrigan & Lynch, 2003).

These have undermined the importance of questionnaire and interview methods which is the most recommended approach for psychological evaluation of suicidal cases in hospitals.

Several Machine Learning approaches have been used to predict suicide ideation based on the information extracted from social media. While this is viable the major limitation is that it addresses the immediate cause of suicide as expressed in the suicide notes rather than the remote cause which is an accumulation of many other factors like loss of loved one, relationship and financial issues, trauma, abuse, etc. Most of these issues manifest in a way of sleep deprivation, loss of interest in pursuing ones passion, social isolation, etc. Most of the risk factors associated with suicide and approaches used by many literatures for suicide ideation prediction are shown in the section that follows.

2. SUICIDE IDEATION DETECTION METHODS

Suicide detection has drawn the attention of many researchers due to an increasing suicide rate in recent years and has been studied extensively from many perspectives. The research techniques used to examine suicide also span many fields and methods, for example, clinical methods with patient-clinic interaction (Venek V. , Scherer, Morency, A, & Pestian, 2017) and automatic detection from user-generated content (mainly text) (O'Dea, et al., 2015), (Ji S. , Yu, Sai-fu Fung, Pan, & Long, 2018). Machine learning techniques are widely applied for automatic detection.

2.1. Content Analysis

Social media provides a platform through which millions of users can connect to share ideas, express their feelings and perform some other activities. With the pull of information generated by social media users on a daily basis one can easily predict their behavioral pattern and be able to make an informed decision regarding their suicidal intents. Many researchers have explored social media contents for suicide risk assessment and detection. Shaoxiong et al. (2018.) explained how supervised learning algorithm can be used for early detection of suicide ideation through exploration of user-generated online contents. Vioulès et al (2018) presented a new approach for quantifying suicide warning signs on individual based on suicide related tweeter posts. Their approach identifies a sudden change in a user's online behavior using natural language processing and martingale framework.

Research has shown that there is a connection between social media communication and the desire by vulnerable individuals to commit suicide (Colombo, Burnap, Hodorog, & Scourfield, 2016). Colombo et al. (2016) studied the characteristics between users and the propagation of their suicidal contents. Their result shows a tightly-coupled virtual community based on the high degree of reciprocal connectivity between the authors of suicidal contents and other studies of Twitter users. Coppersmith et al. (2016) performed an exploratory data analysis of the language pattern and emotions surrounding the suicide attempts of Twitter users who have attempted to take their lives in the past. Masuda et al. (2013) used logistic regression approach to determine user characteristics (both social media related and non-social media related) that contributes to suicide ideation. Their result shows that the number of communities a user belongs, the intransitivity (i.e. paucity of triangles including the user), and the fraction of suicidal neighbors in the social network, contributed the most to an individual suicide ideation.

Li et al. (2016) developed a poison-based model that extracts stressor events from teen's stressful moments using their social media posts. Li's approach even though provided a good ground for research on stressful period and stressor event detection it still has some limitations which is the fact that microblogging platforms lacks sufficient facilities and data required to adequately detect stressful events and stressors in individuals.

2.2. Clinical Method

Over the years researchers have developed psychological suicide risk assessment methods that are based on contact with individuals either through interview or questionnaire for example suicide probability scale (Bagge & Osman, 1998), Depression anxiety Stress Scales-21 (Crawford & Henry, 2003), Adult Suicide Ideation Questionnaire (Fu, Liu, & Yip, 2007) Suicide Affective Behaviour-Cognition Scale (Harris, et al., 2015), etc. These methods even though are effective and professional but are not all encompassing as the interview (Scherer, Pestian, & Morency, 2013) and questionnaire methods (Venek V. , Scherer, Morency, A, & Pestian, 2017) used may put some suicidal population at disadvantage as they might either not be able to access the resources or lack the motivation to use them (Zachrisson, Rodje, & Ietun, 2006; Essau, 2005). On a second note research has suggested that interview and questionnaire method of suicide risk assessment might have some negative impact on individuals showing depressive symptoms (Harris & Goh, Is suicide assessment harmful to participants? findings from a randomized controlled trial, 2016).

2.3. Feature Engineering

The suicidal intent of an individual can be predicted from his or her social media post through text based suicide classification. The texts and data used in suicide predictions can take different forms and features. Machine Learning and Natural Language Procession (NLP) provides useful approach in the manipulation of data and text for extraction of useful information about individuals and their suicidal ideation.

2.3.1. Tabular Features: Tabular data such as questionnaire and structured statistical contents extracted from websites serves as tools for suicidal ideation detection through classification or regression. Many researches have been conducted using tabular features for statistical analysis of questionnaire or tabular data for suicidal ideation detection. Masuda et al. (2013) applied logistic regression using age, gender, community number, homophily and registration period variables to determine the characteristics of user's on and outside social network that might influence their suicide ideation. They found that community, neighbor, intransitivity and social network has great influence on an individual's suicidal ideation. Chattopadhyay et al (2007) applied regression analysis on suicide scenario factors using Pierce Suicide Intent Scale (PSIS). They extracted the risk factors in a tabular form using questionnaire responses gotten from the concerned individuals. Delgado-Gomez, et al. (2012) compared five multivariate techniques with regard to their accuracy in the classification of suicide attempt. These techniques were applied on questionnaire responses from international personal disorder examination screening and Homes-Rahe social readjustment rating scale. Chattopadhyay (2012) used Beck's suicide intent scale (BSIS) to structure data gotten from patient's data sheet for mathematical modeling (using Multilayer Feed Forward Neural Network) method of suicide intent estimation.

2.3.2. General Text Features: Unstructured text consists of features (like knowledge-based features, syntactic features, N-gram features, context and class-specific features) which can be extracted in different forms for use in feature engineering for suicide ideation detection. Many authors have demonstrated how feature engineering can be employed in unstructured text for suicide ideation detection. Wang et al. (2012) showed how a rule-based algorithm can be applied on suicide notes for the extraction of syntactic and lexical patterns for sentiment classification. Liakata et al. (2012) used hybrid approach for detection of emotion in suicide notes. Pestian et al. (2010) used information extracted from patient's suicide notes to understand the patients thought. Abboute et al. (2014) described how suicide related vocabularies can be extracted from Tweeter for prediction of tweets with suicidal contents. Braithwaite et al. (2016) performed a validation check on the use of Machine Learning on Twitter data with a view of suicide prevention. Okhapkina et al. (2017) explained methods that can be adapted for the extraction of Destructive Informational Influence on social network.

2.3.3. Affective Characteristics: Computer Scientists and Mental health professionals have focused their research on affective characteristics of suicidal and non-suicidal individuals as the level of divergent in this trait puts them in the category of being suicidal or not. Many authors have used different means to detect the emotions of an individual in social media. Ren et al. (2016) showed how complex emotion topic (CET) model can be used to detect emotions from social media blogs by employing eight emotion categories and five levels of emotion intensities. Liakata et al. (2012) proposed a hybrid model to detect emotion from suicide notes. Pestian et al (2010) proposed a model to understand a patient's suicidal thought based on the information gotten from his or her suicide note. Their result shows relatively higher classification accuracy in favor of the model as against the trainees and health care professionals.

2.4. Deep Learning

Deep learning has gained wide popularity in many application domains such as computer vision, Natural Language Processing (NLP), crop classification, and medical diagnoses. Its popularity is based on its ability to work on unlabeled and unstructured data. Deep learning has been used extensively by many suicide researchers for suicide ideation detection and prevention. The three popular deep neural networks as shown in figure 1a, 1b, 1c are 1) convolutional neural networks (CNNs), recurrent neural networks (RNNs), and bidirectional encoder representation from transformers (BERT). The online text streams used for suicide ideation detection are usually encoded in vector form using word2vec (Mikolov, Chen, Corrado, & Dean, 2013) and GloVe (Pennington, Socher, & Manning, 2014) the two popular word embedding techniques. The user posts encoded in (2018) were done using user-level CNN with 3, 4, and 5 filter window set. Ji et al. (2018.) applied LSTM and CNN for encoding and classification of user posts for suicide ideation detection. Their model relied on manual labeling of users posts, which in most scenarios are limited in application due to decentralization of the training. In that case semi-supervised or unsupervised learning would be the most suitable method.

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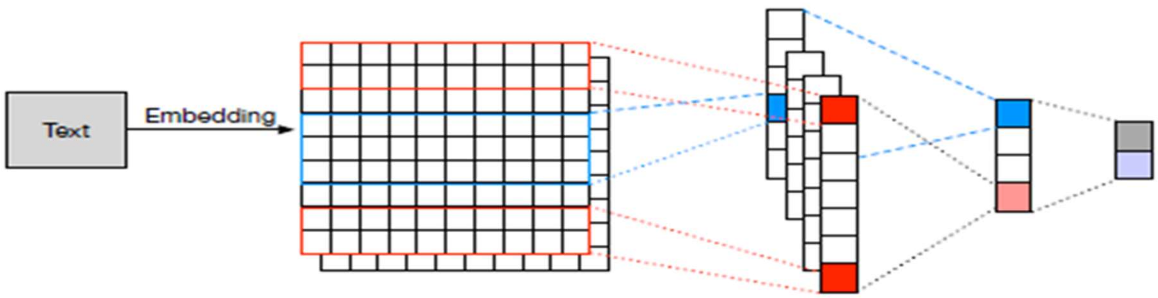
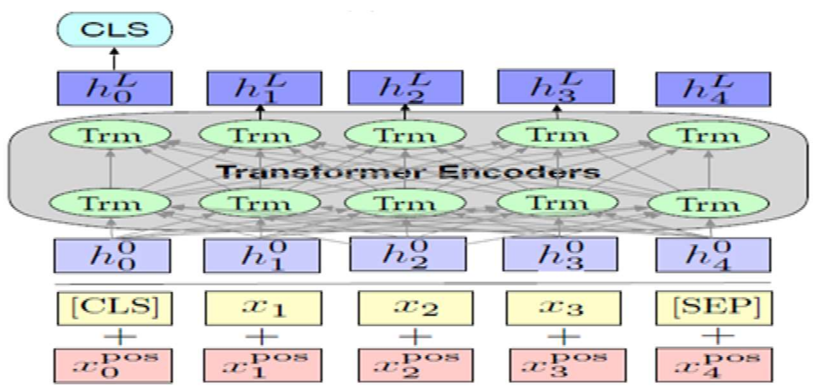
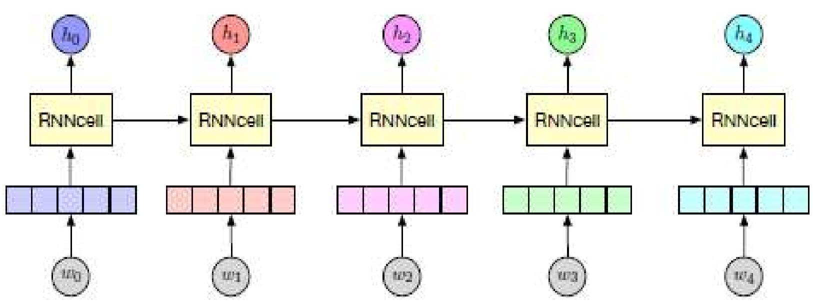


(a) CNN



(b) RNN



(c) BERT

Fig. 1: Deep neural networks for suicidal ideation detection

Deep learning has been used to assess suicide and mental risks in individuals. Adrian et al. (2017) presented a deep learning framework for estimating suicide and mental health risk using user's social media texts. Manas et al. (2019) proposed a Convolutional Neural Network (CNN) based suicide risk prediction using Reddit posts. On a similar note Morales et al. (2019) used deep learning approach to predict suicide risks on individuals based on their posts on Reddit online community.

Matero, et al. (2019) applied open-vocabulary and theoretical features in support forum for suicide risk assessment. They proposed model that separates languages used in suicide specific context from languages used in other forums.

Several approaches have been employed to gain a better performance and prediction efficiency on deep learning for text classification and suicide ideation detection. Gaur et al. (2019) enhanced the performance of their CNN model by representing texts based on suicide related concepts and external knowledge bases. Coppersmith et al. (2018) used GloVe and bidirectional LSTM for capturing text with the highest information sequence.

3. SUICIDE IDEATION DETECTION DOMAIN

Different machine learning techniques have been applied in wide range of suicide ideation detection. The success of any technique depends on the validity and source of the data. Machine learning can be applied on dataset from a wide range of domains, for example questionnaire, electronic health records (EHRs), suicide notes and online user contents. Text messages was used in (2018.) for suicide risk identification. Suicide prevention has been tackled by some researchers using software applications. Berrouiguet et al. (2016) proposed an e-health mobile application for the suicidal patients to access and report their medical conditions to the mental health care providers. Meyer et al (2017) developed a tool called e-pass that helps medical professional detect suicide ideation in patients. Shah et al. (2019) studied the use of profanity, death and other suicide related words in social media videos as behavioural markers for prediction of suicide ideation in individuals.

3.1. Questionnaire

Mental health assessment and disease classifications in mental health cares are based on the following tools: the International Personality Disorder Examination – Screening Questionnaire (IPDE-SQ), International Classification of Diseases version 10 (ICD-10) and Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition (DSM-IV). The testimonies of mental patients and the traits of their mental condition can be accessed using the above tools. The tools guide the mental health professionals in the formulation of interview questions and questionnaires for evaluation of patients with mental conditions or suicide intents.

Delgado-Gomez et al. (2011) compared Barrat's impulsiveness scale version 11 and international personality disorder evaluation screening questionnaire (IPDE-SQ) for their discriminative ability in suicide ideation prediction using Support Vector Machine (SVM). They found that the items in IPDE-SQ have better discriminative ability than items in BIS-II. Delgado-Gomez, et al. (2012) compared the application of five multivariate techniques (linear regression, stepwise linear regression, decision trees, Lars-en and support vector machines) on Holmes-Rahe social readjustment rating scale and the international personal disorder examination screening questionnaire. Harris et al. (2014) studied how the online behavior of suicide-risk individuals differed from non-suicide risk individual using Suicide Behaviours Questionnaire – Revised (SBQ – R). The SBQ – R assesses suicidal behavior based on the following four main attributes: lifetime suicidal behavior, past-year suicidal ideation, disclosing suicidal plans and perceived likelihood of future suicide.

Sueki (2015) carried out a survey to understand how tweeter log of young internet users can help in predicting suicide in individuals by studying the relationship between suicides related tweets and suicide behavior. The questionnaire in his research was analyzed using logistic regression.

3.2. Electronic Health Records

Electronic health record (EHR) are vital digital medical information (like diagnoses, medications, treatment plans, allergies, emergency visits, history, demographic information, etc) kept about a patient that can enable health care providers make vital decisions about the patient. It provides volume of medical information that can be utilized for suicide ideation detection using machine learning techniques. Utilizing this tool for suicide attempt prediction is usually challenging due to data sparsity, record heterogeneity and variation in clinical series. Sometimes healthcare policies review might influence the recording procedure and affect the utility of the tool for suicide attempt prediction.

Suicide risk prediction using EHR has attracted several research efforts. Tran et al. (2013) proposed a machine learning framework that tackles suicide risk prediction using feature extraction, feature selection, risk classification and risk calibration procedure. They applied bank of multi-scale convolutional filter on features generated from the patient's clinical history.

There are several works of predicting suicide risk based on EHRs (Hammond, Laundry, OLeary, & Jones, 2013; Walsh, Ribeiro, & Franklin, 2017). Tran et al. (2013) proposed an integrated suicide risk prediction framework with a feature extraction scheme, risk classifiers, and risk calibration procedure. Explicitly, each patient's clinical history is represented as a temporal image. Iliou et al. (2016) proposed a data preprocessing method to boost machine learning techniques for suicide tendency prediction of patients suffering from mental disorders. Nguyen et al. (2016) explored real-world administrative data of mental health patients from the hospital for short and mediumterm suicide risk assessments. By introducing random forests, gradient boosting machines, and DNNs, the authors managed to deal with high dimensionality and redundancy issues of data. Although the previous method gained preliminary success, Iliou et al. (2016) and Nguyen et al. (2016) have a limitation on the source of data which focuses on patients with mental disorders in their historical records. Bhat and Goldman-Mellor (2017) used an anonymized general EHR dataset to relax the restriction on patient's diagnosis-related history and applied neural networks as a classification model to predict suicide attempters.

3.3. Suicide Notes

Suicide notes are the written notes left by people before committing suicide. They are usually written on letters and online blogs and recorded in audio or video. Suicide notes provide material for NLP research. Previous approaches have examined suicide notes using content analysis (Pestian, et al., 2012) , sentiment analysis (Pestian, et al., 2012; Wang, Chen, Tan, Wang, & Sheth, 2012) , and emotion detection (Liakata, Kim, Saha, Hastings, & Rebholzschuhmann, 2012). Pestian et al. (2012) used transcribed suicide notes with two groups of completers and elicitors from people who have a personality disorder or potential morbid thoughts. White and Mazlack (2011) analyzed word frequencies in suicide notes using a fuzzy cognitive map to discern causality. Liakata et al. (2012) employed machine learning classifiers to 600 suicide messages with varied length, different readability quality, and multi-class annotations.

Emotion in text provides sentimental cues of suicidal ideation understanding. Desmet et al. (2013) conducted a fine-grained emotion detection on suicide notes of 2011 i2b2 task. Wicentowski and Sydes (2012) used an ensemble of maximum entropy classification. Wang et al. (2012) and Kovaˇcevi´c et al. (2012) proposed hybrid machine learning and rule-based method for the i2b2 sentiment classification task in suicide notes.

In the age of cyberspace, more suicide notes are now written in the form of web blogs and can be identified as carrying the potential risk of suicide. Huang et al. (2007) monitored online blogs from MySpace.com to identify at-risk bloggers. Schoene and Dethlefs (2016) extracted linguistic and sentiment features to identity genuine suicide notes and comparison corpus.

3.4. Online User Content

The widespread use of mobile Internet and social networking services facilitates people's expressing their life events and feelings freely. As social websites provide an anonymous space for online discussion, an increasing number of people suffering from mental disorders turn to seek for help. There is a concerning tendency that potential suicide victims post their suicidal thoughts on social websites like Facebook, Twitter, Reddit, and MySpace. Social media platforms are becoming a promising tunnel for monitoring suicidal thoughts and preventing suicide attempts (Robinson, et al., 2016) Massive user-generated data provide a good source to study online users' language patterns. Using data mining techniques on social networks and applying machine learning techniques provide an avenue to understand the intent within online posts, provide early warnings, and even relieve a person's suicidal intentions.

Twitter provides a good source for research on suicidality. O'Dea et al. (2015) collected tweets using the public API and developed automatic suicide detection by applying logistic regression and SVM on TF-IDF features. Wang et al. (2016) further improved the performance with effective feature engineering. Shepherd et al. (2015) conducted psychology-based data analysis for contents that suggests suicidal tendencies in Twitter social networks. The authors used the data from an online conversation called #dearmentalhealthprofessionals.

Another famous platform Reddit is an online forum with topic-specific discussions has also attracted much research interest for studying mental health issues (Choudhury & De, 2014) and suicidal ideation (Bashir, 2016). A community on Reddit called SuicideWatch is intensively used for studying suicidal intention (Choudhury & De, 2014), (Ji S. , Yu, Fung, Pan, & Long, 2018.). Choudhury et al. (2014) applied a statistical methodology to discover the transition from mental health issues to suicidality. Kumar et al. (2015) examined the posting activity following the celebrity suicides, studied the effect of celebrity suicides on suiciderelated contents, and proposed a method to prevent the high-profile suicides.

Many pieces of research (Huang, et al., 2014), (Huang, et al., 2015) work on detecting suicidal ideation in Chinese microblogs. Guan et al. (2015) studied user profile and linguistic features for estimating suicide probability in Chinese microblogs. There also remains some work using other platforms for suicidal ideation detection. For example, Cash et al. (2013) conducted a study on adolescents' comments and content analysis on MySpace. Steaming data provides a good source for user pattern analysis.

Vioul`es et al. (2018) conducted user-centric and post-centric behavior analysis and applied a martingale framework to detect sudden emotional changes in the Twitter data stream for monitoring suicide warning signs. Ren et al. (2016) use the blog stream collected from public blog articles written by suicide victims to study the accumulated emotional information.

4. SUMMARY AND CONCLUSION

Applications of suicidal ideation detection mainly consist of four domains, i.e., questionnaires, electronic health records, suicide notes, and online user content. Table II gives a summary of categories, data sources, and methods. Among these four main domains, questionnaires and EHRs require self-report measurement or patient-clinician interactions and rely highly on social workers or mental health professions. Suicide notes have a limitation on immediate prevention, as many suicide attempters commit suicide in a short time after they write suicide notes. However, they provide a good source for content analysis and the study of suicide factors. The last online user content domain is one of the most promising ways of early warning and suicide prevention when empowered with machine learning techniques. With the rapid development of digital technology, usergenerated content will play a more important role in suicidal ideation detection. Other forms of data, such as health data generated by wearable devices, can be very likely to help with suicide risk monitoring in the future. TABLE I: Summary of studies on suicidal ideation detection from the views of intervention categories, data and methods

Table I: Summary of studies on suicidal ideation detection from the views of intervention categories, data and methods

Categories	self-report examination (Venek V. , Scherer, Morency, Rizzo, & Pestian, 2017) face-to-face suicide prevention (Scherer, Pestian, & Morency, 2013) automatic SID 2.3.2, 2.3.3, 2.3.4
Data	questionnaires 2.3.1 suicide notes 2.3.3 suicide blogs 2.3.3 electronic health records 2.3.2 online social texts 2.3.4
Methods	clinical methods (Sikander, et al., 2016), (Just, et al., 2017), (Jiang, Wang, Sun, Song, & Sun, 2015) mobile applications (Tighe, et al., 2017) content analysis 2.2.1 feature engineering 2.2.2 deep learning 2.2.3
Critical issue	suicide factors (Hinduja & Patchin, 2010), (Joo, Hwang, & Gallo, 2016), (Vioulès, Moulahi, Azé, & Bringay, 2018), (C, Nock, & K, 2014) ethics (Andrade, de Pawson, Muriello, Donahue, & Guadagno, 2018), (McKernan, Clayton, & Walsh, 2018), (Linthicum, Schafer, & Ribeiro, 2019) privacy (Andrade, de Pawson, Muriello, Donahue, & Guadagno, 2018)

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