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Applying artificial intelligence to detect depressive disorders in adolescents via social network generated contents

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***Abstract*---**Depressive disorders and suicide are one of the leading causes of death in most countries around the world; it is one of the three most common causes of death in a group of young people, but so far, no methods have been developed for diagnosing suicidal tendencies. In this connection, the problem of developing methods for identifying people prone to suicidal behavior is becoming especially topical. One of the directions of such research is the search for typological features of the speech related to depression using the methods of mathematical linguistics, automatic text processing and machine learning. In foreign science, the texts of people that were motivated by depression are studied using methods of automatic text processing, machine learning methods, and models that are constructed to allow to classify whether the text is related to depression or not. It seems obvious that in order to develop methods for identifying people who are prone to depression and suicide, it is necessary to analyze not only suicide notes, but also other texts

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created by people who have committed suicide. The purpose of this work is to build a model of machine learning, apply teaching methods with and without a teacher, then select the most efficient algorithm for the task to classify whether the text is connected to depression and suicide using comparative analysis. Our research contributes to detection of depressive content that can cause suicide. Obtaining highest result for 95% of f1-score for Random Forest with tf-idf vectorization model, in conclusion we may say that K-means using tf-idf shows impressive results, which is only 4% lower in f1-score and precision.

***Keywords*---**depression, healthcare, mental health, social networks, artificial intelligence.

Introduction

It is one of the three leading causes of death in a group of young people (15-24 years old), but there are no methods that have been developed so far that can diagnose suicidal tendencies. Although suicide is one of the leading causes of death in most countries around the world, it is also one of the three most common causes of death in a group of young people. In this context, the challenge of devising strategies for locating those who are more likely to engage in depression conduct is becoming an issue of particular relevance. The search for typological aspects of speech associated to depression using the methodologies of mathematical linguistics, computerized text processing, and machine learning is one of the routes that this kind of study might go in. Methods of automatic text processing (natural language processing), methods of machine learning, and models that are constructed to allow for the classification of whether or not the text is related to depressive disorder can be used in the study of the writings of people whose suicides were motivated by suicidal thoughts. These studies focus on the suicide notes left behind by the deceased. It seems obvious that in order to develop methods for identifying people who are prone to suicide, it is necessary to analyze not only suicide notes, which are typically brief texts, but also other texts created by people who have committed suicide. This is because suicide notes are the most common form of text left behind by people after they have taken their own lives. Building a model of machine learning, using training techniques with and without a teacher, and selecting the most effective algorithm for the goal of classifying if the text is linked to suicide using comparative analysis are the objectives of this study. Our study makes a contribution to the identification of depressed content that may lead to suicide, as well as to the facilitation of such individuals receiving competent assistance from psychologists. K-means (Unsupervised) using tf-idf shows impressive results, which are only 4% lower in f1-score and precision than Random Forest (Supervised) using tf-idf vectorization model, which obtained the highest result for 95% of f1-score. In conclusion, we may say that K-means (Unsupervised) using tf-idf shows impressive results.

Related Works

According to information provided by the World Health Organization, more than 800,000 people pass away each year as a result of suicide. This equates to one person taking their own life every 40 seconds. However, according to the information that is currently available, only thirty percent of those who have taken their own lives had previously disclosed their intentions (World Health Organization, 2014). As a result, there is an objective need to create strategies that are geared at detecting persons who are likely to engage in suicidal conduct and preventing them from attempting suicide. The analysis of a person's speech production, including the formal grammatical level, which is beyond the control of consciousness, is the most valuable diagnostic tool that reveals the peculiarities of the personality psyche, including its tendency to engage in suicidal behavior. This is because the analysis of a person's speech production is the most valuable diagnostic tool that reveals the peculiarities of the personality psyche.

Social networks are responsible for the production of major information flows that are characterized by a high degree of dynamism and size. The capacity of social networks is continually growing, and with with it comes a rise in the speed of data transmission, which in turn leads to an increase in their processing. The information obtained from social networks, which at first glance appears to be dispersed, can be distributed according to a huge number of criteria, both those that are common to certain groups of users and those that are personally oriented. This is made possible by the utilization of modern technologies for the analysis of large amounts of data.

In this study, supervised and unsupervised learning methods are contrasted on order to detect suicidal thoughts in the popular social network Vkontakte among teenagers and young people in Kazakhstan. After Facebook, the social networking service known as VK (formerly spelled VKontakte) is the second most popular one in Europe. In the next part, we will conduct a literature study taking into consideration other relevant publications in this field. In Section 3, the research approach is broken down and discussed. In the next section, we go into the experimental assessment and examine the findings in terms of the accuracy of suicidal and non-suicidal post classification as well as the selection of the optimal algorithm for the detection of suicidal thought.

Literature Review

Pre-suicidal Factors

The most recent and thorough studies on the effects of social media, particularly Facebook, Twitter, and Instagram, on our mental health is available in the BBC Future review (Brown, 2018). Internet social networks are used by three billion individuals globally, or around 40% of the population (Naslund et al., 2016). We share posts, images, and reply to friends' postings on them every day, spending an average of two hours doing so. Nearly half a million tweets and photographs are sent from social media platforms every minute to Snapchat. Social media significantly affects our life, thus it's critical to comprehend how they effect us.

Stress

We often vent our outrage on social media sites about anything from bad services to political issues. This gives us a way to vent, but it also fills our news feed with unending negative content. Recent studies looked at whether social networks truly relieve stress or, on the contrary, exacerbate it (Escobar-Viera et al., 2018; Waytz, A., & Gray, 2018; Villalonga-Olives & Kawachi, 2017; Wang et al., 2018).

Anxiety

Additionally, the researchers looked at how social networks affected the general anxiety level. According to a research in the journal Computers and Human Behavior (Computers and Human Behaviour), users of seven or more social media sites experience three times as much overall anxiety as those who use two or fewer platforms (Primack et al., 2017).

Depression

Although some earlier studies (Frison & Eggermont, 2016; Twenge et al., 2018; Andreassen et al., 2016) indicated a connection between depression and social media usage, more recent research in this field supports the reverse. For instance, research involving more than 700 students revealed a correlation between depressive symptoms including poor mood, inferiority complex, and despair, and the quality of online communication (Tan et al., 2016). Depressive symptoms were more prevalent in individuals for whom virtual connection provided predominantly unpleasant feelings. The risk of sadness and anxiety was three times greater among those who utilized many social media sites, according to a comparable research done in 2016 with 1,700 participants (Primack et al., 2017; Lin et al., 2016; Hswen et al., 2018). Virtual harassment and an inaccurate perception of other people's life were two of the main causes mentioned by the researchers (Fox & Moreland, 2015; Ersoy, 2019; Olenik-Shemesh & Heiman, 2017).

However, researchers are also looking at how social media helps identify depressive signs, making it easier to get care right away (Guntuku et al., 2017; Shen et al., 2017; Yazdavar et al., 2017; Shen et al., 2018; Islam et al., 2018). In response to a request from Microsoft, researchers polled 476 Twitter users and examined their social media accounts, focusing on the tone of messages, feelings, the manner in which users interacted with one another, and any indications of depressed behavior. With the use of this information, they created a questionnaire that gives us the ability to identify the likelihood of developing depression seven out of ten times before any symptoms occur.

Loneliness

According to a research by the American Journal of Preventive Medicine, which included 7,000 participants between the ages of 19 and 32, those who spend a lot of time on social media feel socially isolated more than twice as often. They lack social engagement, a feeling of belonging to a group, and committed relationships.

Researchers claim that for certain individuals, social networks stifle intimate connections and increase feelings of loneliness. "An inflated perception of the happiness and prosperity of friends and acquaintances might result from an idealized perspective of their life. These ideas exacerbate social isolation."

How are Social Networks and Dysmorphophobia Related?

Social networks are often accused of promoting physical dysmorphophobia, which is the dislike of one's own body and the hunt for manufactured faults as well as eating disorders and other mental health issues. The claims' core idea is that Instagram photographs affect people's perceptions of their bodies, making their own eventually seem "different" to others (Tiggemann et al., 2018; De Vries and Vossen, 2019; Tiggemann and Barbato, 2018). More and more plastic surgeons claim that social media is spurring an increase in surgeries. Patients now visit them with snapchat filters instead of celebrity photographs, which allows us to talk about a new kind of dysmorphophobia. On the other hand, body positivity works as intended: social media platforms enable people whose appearance has not previously been represented in the media space to tell the world about themselves, appear in commercials, take the stage, and use their own example to show that their body is deserving of respect.

According to research, those who had symptoms of depression exhibited the following behaviors on social media: They utilize social media to compare themselves to other users' "better" selves. This trend is most often seen on Instagram, where individuals upload only successful photographs to portray a prosperous existence and leave reality in the background; Symptom 2: They use social media on a regular basis, reaching the point of "addiction" (this condition was identified based on survey results in which students said "yes" to the phrases "you sought to reduce the use of social media" and "this had a negative influence on your job / study"). They were anxious after learning that their unsuccessful images had been posted on social media. This often made pupils anxious and sometimes hostile. Symptom 4 These pupils seldom ever post pictures of themselves with others. According to the study's authors, persons with depression often have a tendency to distance themselves from others, which is why these people are less likely to upload photos of themselves with others.

Applying AI in Suicidal Ideation Detection and Suicide Prevention

The fact that suicide is a prevalent cause of mortality for teens and young people (Glodstein et al., 2018; Ahad & Shah, 2018; Arendt et al., 2019; Kapka-Skrzypczak, 2019; John et al., 2018; Memon et al., 2018) is what disturbs people the most. There have long been initiatives to educate technology how to prevent suicide. A team of academics tried (quite effectively) to examine MySpace.com user information in 2007 to find those who are close to taking their own lives. It is known, among other things, that machine learning algorithms are far more accurate than experienced physicians in telling a suicide note apart from a false one (78% accuracy vs 63%), and suicidal tendencies may be detected in a variety of ways, such as the length of vowels used in speech. The quest for these is not entirely new; a recent study revealed that after fifty years of research on suicide, experts have made no appreciable progress in forecasting it. Traditional risk

variables, such as depression, stress, and drug use, have been shown to be less accurate than random guessing during the previous 50 years. The primary issue with past research is seen to be an incredibly limited methodology: the majority of them only address one risk element and give no consideration to the complexity of their combinations.
Automatic examination of brain activity may be used to identify a person's propensity for suicidal conduct. It was replaced by American researchers who used machine learning techniques to analyze data from fMRI scans of probable suicides. The new algorithm had a 91 percent accuracy rate in identifying those who were suicidal. In the journal Nature Human Behaviour, the paper was published (Just et al., 2017; Omarov et al., 2018). Suicidal teenagers are identified through machine learning of brain representations of emotion and suicide.

Recent research suggests that we might uncover the neurobiological conditions for establishing the notions of the actual world — how tangible conceptions are produced and retained in our mind — by examining patterns of brain activity. For instance, the parahippocampal gyrus, which is in charge of processing information about scenes of reality, is active during the interpretation of the notion of "home." The goal of the current study was to discover if there are variations in brain activity between those who are healthy and those who have suicidal inclinations while describing various emotional concepts (Omarov et al., 2016). If so, could these differences be used to identify a person's suicidal tendencies.

When comparing 17 healthy persons to 17 people who had suicidal thoughts, researchers used machine learning based on the naive Bayes classifier to identify voxels of the variations in activation. Six concepts—"death," "cruelty," "trouble," "carelessness," "good," and "praise"—where activation of them is most varied between the two groups were identified by the researchers. 51 women with illnesses such schizophrenia, schizoaffective disorder, bipolar disorder, and depression participated in a longitudinal research at Indiana University. The standard index of suicidal thoughts (SI) was assessed in each patient throughout their course of therapy. They also measured the amount of gene expression, selecting those whose expression differs most between people with the highest SI and those without suicidal thoughts for future investigation.

The most trustworthy indicators of suicidal risk were found using probabilistic analysis of the genetic information bases included in a few chosen genes. The area under the ROC curve was used to determine how successful the suggested diagnostic approaches were (ROC AUC). This percentage was 78 percent for future hospitalizations for suicidality and 82 percent for UP-Suicide when predicting SI, (Onalbek et al., 2013).

The British Journal of Psychiatry's June 2017 edition has a significant section on suicide prevention and suicide prediction. 39 risk scores that are used to predict suicide behavior were subjected to a systematic review and meta-analysis by Carter and colleagues (Carter et al.). The study's findings led to the conclusion that these measures' positive predictive values—which ranged from 5.5% for suicide to 35.9% for a combined outcome—were too low to be utilized to guide therapeutic intervention choices. As an alternative, the authors suggest a clinical evaluation to pinpoint changeable risk variables and implement particular therapies meant for distinct subgroups of self-harmers (Omarov et al., 2017).

It is now possible to predict with 80% accuracy which patient would try suicide in the following two years according to a ground-breaking investigation that was carried out by researchers at the University of Florida. Jessica Ribeiro, the principal author, just published a new study in Clinical Psychological Science. The study's findings show that machine learning can predict the likelihood of a suicide attempt for a specific individual two years in advance with an accuracy of 80–90%. The algorithms' accuracy improves even more as the suicide attempt gets closer; for patients in the general hospital, it reaches 92% a week before the attempt.

In contrast to a recent analysis of 50 years of research (by Joseph Franklin) in the subject of suicide prediction, which revealed little advancement in this area, Ribeiro's work is very striking. The unexpected outcome of the Franklin test gave rise to the Ribeiro project. Colin Walsh, Franklin, and Ribeiro all worked together to analyze a lot of data. More than 3200 individuals who attempted suicide were found in this database. Similar medical data from thousands of suicidal persons were important information.

After analyzing all of this data, machine learning algorithms were able to "discover" which subsets of the tales best predicted future suicide attempts. According to Ribeiro, "the computer determines the ideal mix of risk variables." "What matters most is how these variables and this algorithm interact as a whole. With the use of these algorithms, we may possibly condense hundreds of pieces of information from a patient's medical history into information that is therapeutically useful. The development of a "alarm system" for doctors who recognize patients at risk for suicide conduct may be aided by such useful data. According to study, between 60 and 90 percent of those who died by suicide saw a doctor during that year, but the physicians failed to recognize the risk of suicide. In order to identify people who are at risk of suicide, effort is now being done in the United States to develop national and worldwide e-case histories for study in the future. This software has already been made available for their own databases by the US Department of State and the Department of Veterans Affairs (Altayeva et al., 2017).

The Korean government made the decision to use a Facebook application called AI Saving Lives to combat the rising suicide rate in the nation. It tracks and analyzes user behaviour in social networks and instant messengers using machine learning techniques. When this kind of information is found, Facebook's algorithm is also able to recognize videos, which people who commit suicide often record before they pass away (Mussiraliyeva et al., 2020).

An algorithm that can determine a person's propensity for suicide has been developed by researchers from the University of Cincinnati, University of Colorado at Denver, University of Southern California, and Princeton University. Suicide and Life-Threatening Behavior is the journal where the study's findings are published. With an accuracy of up to 93%, the machine learning system was able to separate patients with suicidal inclinations from mentally ill and healthy individuals. One of the study's authors, Professor John Pestian, believes the findings "convincingly suggest that sophisticated technology may act as a decision support tool that will allow physicians and social workers to diagnose and prevent suicide conduct." "Medical facilities use technology to great effect, but those who deal with mentally ill individuals do not benefit from it to the same extent. Only now, he continues, can our algorithms assist these professionals.

Computers have long been trained by scientists to recognize suicidal inclinations. Eight years ago, robots were able to differentiate actual notes from simulations. Eleven years ago, researchers developed software that could identify emotions in suicide notes. In 2015, researchers examined individuals in-person, rather than after their deaths, using a small sample of 60 patients at a single medical facility. The first dispersed multicenter study is the subject of a new publication. 379 individuals from the Princeton Public Hospital, the Medical Center of the University of Cincinnati, and the Children's Hospital of Cincinnati all attended. Suicidal, mentally ill but not suicidal, and healthy participants were divided into three groups (control group). People with a mental illness were deemed to be more likely to commit suicide; those who were within 24 hours of an attempt or had the intention to do so went to an ambulance or a psychiatric facility.

The intensity of mania, the severity of suicidal symptoms, and depression were all assessed using standardized assessments on the patients. Then came the interview, during which the doctor probed the patient on their feelings of hope, secrets, and anxieties. plus others. The scientists captured footage of their interactions. In order to discover the hypothesis with the least actual error, they decoded the interviews, assembled a "dictionary" of important phrases and sound characteristics, and trained a computer learning technique known as the "support vector machine" on a portion of this data.

The remaining recordings and interview transcripts were then "fed" to the computer. It found determined that the system accurately separates patients into three groups with at least 70% accuracy. One linguistic or acoustic aspect of speech, or both combined, might be examined by the algorithm. The system achieved an accuracy of 93 (text alone), 79 (audio solo), and 92 (text Plus audio) percent when comparing suicidal patients with a control group. He was able to distinguish mentally ill persons from suicidal people in 79 (text), 76 (audio), and 81 (text and audio) percent of the instances. It's interesting to note that accuracy varied depending on the use of acoustic information.

Recent studies have analyzed texts from diaries, letters, and lifetime interviews with persons who have committed suicide using these software tools. It should be noted that these works merely assert that there are statistically significant differences between the texts of suicides and non-suicidal people, rather than posing the task of developing methods for diagnosing a tendency to suicidal behavior based on a quantitative analysis of speech products. The LIWC software is the primary text analysis tool used in these studies.

The problem of creating a mathematical model that categorizes the texts as belonging to suicides or to people in the control group is also posed. The research did, however, greatly increase the list of text properties. Using contemporary tools for artificial language processing, texts were labeled. A classifier was created using machine learning techniques, and it had a 70.6% accuracy rate. The findings demonstrate the basic feasibility of addressing the issue of diagnosing the risk of suicide conduct based on the study of quantitative analysis of texts using NLP approaches and mathematical statistics, even if the classifier's accuracy is obviously far from ideal. As the study's authors correctly note, expanding the corpus of texts and the set of analytical parameters is important to increase the model's accuracy.

Features Engineering

Without a question, social networks have ingrained themselves into the lives of billions of people, making life without them impossible to conceive. Social networks are used to read the latest news and are a vast platform for information exchange, in addition to being used to communicate with friends, family, and other acquaintances. It is no secret that both big businesses and small business owners use social media. Social networks have emerged as one of the most important marketing platforms with the rapid expansion of the Internet. Indeed, there is a wide range of demographics and age groups represented among social network users.

You may effectively market your product on social networking sites without doing a thorough audience study, but you will profit much more if the target user has certain demographic characteristics, interests, hobbies, or behaviors that are based on social network data. Such information enables, for instance, the provision of customised product offers that are more appropriate for this user or the identification of prospective customers so that more active sales techniques may be used. Each user often has a name, age, location, and a brief description of their hobbies or ties to other social networks in many services. Nevertheless, sometimes, this is insufficient, or the data may not be accurate. To do all of this, data gathering and processing technologies must be improved.

Basic user classification model

- Profile, behavior, text content, and data from the social networks itself (for instance, time of visits, number of subscribers subscriptions), are the four basic forms of data that indicate information about the user on social networks.
- These kinds are sufficient to retrieve characteristics from a multipurpose classification model. We deal with the following difficulties:
- A broad evaluation of the trait's relative influence, its dependability, and a generalization of prospective user categorization options.
- Examining the use of linguistic data for user classification.

Signs from user profile

Many services automatically show profile details including user name, location, and a succinct description of the individual. Additionally, many well-known social networking APIs provide users access to other data like the quantity of subscribers, friends, publications, etc. However, there are a number of issues that might arise when collecting data from social networks: limiting or restricting access to facilitate information gathering automatically. Data privacy - Users often specify privacy preferences, which prevent outside access to numerous personal characteristics. Data gathering is highly difficult because of the poor data structure of certain social networks, which either lack an API or have stringent limits. You must "manually" get HTML and parse the page structure to do this.

Signs from user profile

Statistics on interactions with the service, such as the average daily message volume, response rates, and repeat publishing rates, are indicators of user activity. Such information could work well for the model's training. For instance, data demonstrate that individuals who produce publications seldom have more original material compared to those who do so more often, and articles include a URL to third-party websites.

Text Content

The primary subjects of interest to readers are covered in text material. Users may be categorized using simple text information such as comments, blogs, chats, and search sessions. We then examine the fundamental characteristics of textual content.

Modeling by Topic

Considering n classes, where each ci represents a group of Si users. A score for each of the classes is given to each term that is allocated to at least one user. The conditional probability of the class is used to determine the score using the following formula:

$$proto(w, c_i) = \frac{|w,\ S_i|}{\sum_{j=1} |w,\ S_j|} \tag{1}$$

where | w, Si | this is the number of words issued by w for all users of the class ci. For each class of users, k thematic words with a high score are saved. The n * k thematic words are collected from all classes and serve as signs representing a specific user: for each thematic word wp, an estimate is assigned to user u.

$$f_{proto_{c(u)}} = \frac{\sum_{wp \in WP} |u,\ wp|}{\sum_{w \in W_u} |u,\ w|} \tag{2}$$

Wp is a set of thematic words for class c.

Hashtag classification

You may use hashtags on numerous social media platforms to identify the primary subject of an article. To make it easier to find information across sources with comparable content, the same or similar hashtags are often used. Similar to how topic words are classified, hashtag classification also happens. Given that the set is Si for class ci, it will include all of the publication's hashtags. Then, using Formula 1, you may get a collection of hashtag themes. In order to determine the qualities, use algorithms 2 and 3 to compute hashtags with high grades for each class.

Hashtag classification

The user's interactions with other social network users, his responses, reposts, and publications he enjoys play a big part in categorisation.

Friends

It is obvious that individuals who like automobiles are more inclined to include acquaintances who share their interests and join organizations that focus on automobiles. Users of other classes probably have the ability to share certain accounts of friends as well. The same topic phrase categorization process, formula 1, may be used to load a set of classes of friend profiles F. The number of profiles the user is subscribed to; the percentage of F profiles that are subscribed to u; and the percentage of accounts subscribed to u are the next attributes you need to get for this user.

Answers, comments and reposts

The indicator here indicates that the user has a propensity to remark, share, and contribute to the material of individuals or groups of interest using the same logic as with friends. The similar classification technique, using hashtags and theme terms, is feasible.

Communities

Humanity often comes together in different groups of interest, profession, and social circle in the actual world. The similar image may be seen on social media. Another crucial classifying criteria is an examination of the user communities on social media platforms. Systems of recommendations, filtering, and spam detection, among many other uses, use data on communities and social networks on a worldwide scale. Social network groups are often internally classified, which makes it much easier to categorise persons that join them.

Materials and Methods

Definition of the terms "danger" and "depression" are essential before categorizing information as suicidal or depressing. The definition of a group of keywords is one of the answers. It is a technique for figuring out the different forms of information and it is used in the created software package. A list of keywords was created for the definition, and material from the social network VKontakte was examined using these keywords. The software program determines if the material is appropriate for further investigation based on the presence or absence of the given keywords in the text.

Depending on the information's source, several methods of getting it may be used, but they all adhere to the same basic building principles. The primary goal of the software component that collects data from open sources is to carry out tasks swiftly and effectively. Use the built-in techniques for getting information from sources (API), if there are any, to get the best performance. In the absence of such approaches, it is important to acquire and extract the required data from HTTP requests.

The software package consists of three distinct modules:

1. Information collection module - collects information from open sources and transmits it for further processing.
2. Keyword search module - locates keywords in a vast volume of information.
3. Document rating module - determines if the information is risky.

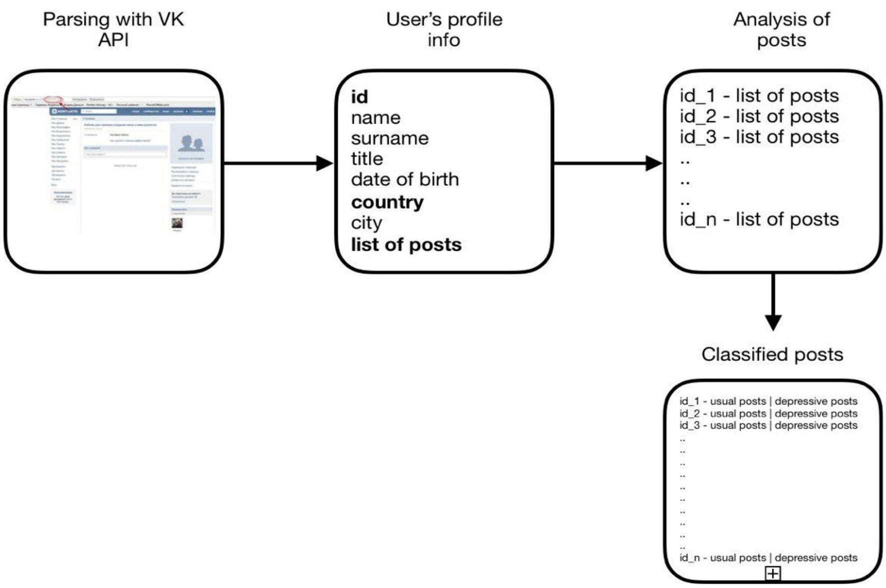

Figure 1. Data division of training and testing dataset

For those with depression of different severity levels, including severe, chronic, manic, persistent depressive disease, and so forth, we gathered 35,000 texts in Russian. A homogenous text basis, separated into a training base for learning algorithms and a test base for assessing algorithm performance, was also created using roughly 50,000 personal postings from social networks with unfavorable sentiments on numerous themes. As shown in Figure 2, the training and testing datasets were separated by 74.5% to 24.5%.

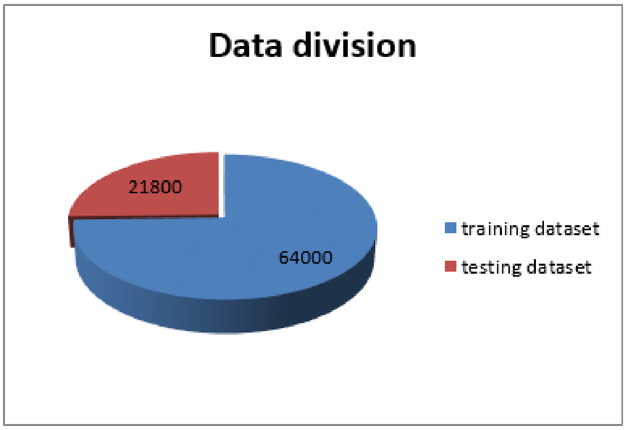

Figure 2. Data division of training and testing dataset

Our psychologists found three potential reasons of suicide based on a comprehensive study of the text corpus as well as the key themes and emotions:

1. Asking for help is a desperate effort to get others to notice how they are feeling.
2. Avoidance - the incapacity to put up with any more agonizing remorse or embarrassment over unethical behavior.
3. The protest, which often include the expression of angry and accusatory feelings, is a protest against challenging family issues. A written message is often addressed to a particular individual or group of individuals.

Suicide is not an act of impulsivity, and planning for it might take up to a year, during which time a person will exhibit symptoms of their disease. To identify this risky moment, we apply sentiment analysis.

Results and Discussion

With supervised learning, we employed Random Forest, Gradient Boosting to find sad articles. While using K-means with a 2-cluster model for teaching without a teacher (Omarov et al., 2020).

Data Preprocessing

First, lemmatization—the process of removing just word ends and reverting to a word's lemma, or vocabulary form—was applied to all texts. The Yandex lemmatizer "MyStem" was employed since it produced great results for lemmatizing words in the context of the Russian language. The stop word was then eliminated using the nltk stop word package, which reduced possible noise in the data. Additionally eliminated were numbers, special characters, and non-Cyrillic letters. To represent texts in a vector space for arithmetic operations on the full data structure, the pre-processed texts were secondarily vectorized. The vector view is faster. The TF-IDF and Word2Vec models were employed to vectorize texts.

Term Frequency-Inverse Document Frequency, or TF-IDF, is an acronym that essentially denotes the weight of a term in a package or collection of data. Term frequency (TF) and reverse document frequency are two notions included in TF-IDF (IDF). Deep learning method Word2vec uses a two-layer neural network. Google Word2vec translates huge data into vector space using the data. Words with similar meanings are grouped together, and the distance between words also has a similar meaning, thanks to Word2vec, which essentially places words in feature space where their placement is dictated by their meaning.

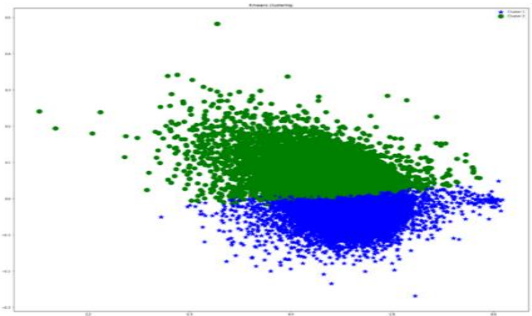

Figure 3. A graphical representation of the word2vec vectors in a 2D space, where green labels are depressive posts, and blue labels are regular posts

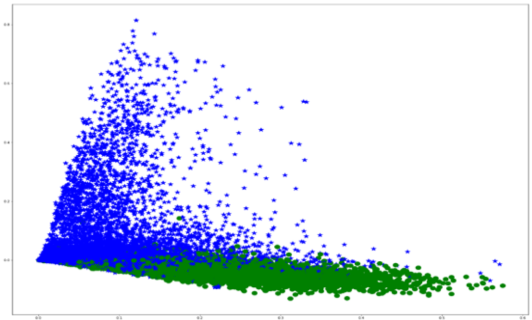

Figure 4. Graphic representation of tf-idf vectors in 2D-space, where green marks are depressive posts, and blue marks are normal posts

the main characteristics of results as accuracy, precision, recall, and F1-score were given in Table 1.

Table 1
Supervised learning algorithm for suicidal ideation detection

Algorithm	Accuracy	Precision	Recall	F1-score
Gradient Boosting word2vec	88%	89%	89%	89%
Random Forest with word2vec	87%	89%	88%	88%
Gradient	88%	88%	87%	85%

Boosting with tf-idf				
Random Forest with tf-idf	88%	86%	86%	86%

The best classifiers for the given issue, according to Table 1, are Gradient Boosting with tf-idf and Random Forest with tf-idf. With 96% accuracy, Random Forest's tf-idf algorithm is the best supervised learning system for identifying suicidal thoughts. When comparing the f1-score outcomes of several algorithms, we can see that the Random Forest with tf-idf method yields a result of 95%, which is excellent for the job at hand. The Receiver Operating Characteristic (ROC) curve with cross-validation was constructed to ensure the accuracy of our method. To comprehend a performance measurement for a classification issue at multiple threshold levels, a ROC curve was used.

Since it is preferable to maximize the true positive rate while lowering the false positive rate, the "steepness" of ROC curves is also crucial. The ROC curve of various train and test datasets, produced by K-fold cross-validation, is shown in Figure 5. When the training set is divided into distinct subsets, it is feasible to compute the mean area under each curve and observe the variation of the curve. This basically illustrates how changes in the training set impact the classifier output and how distinct the splits produced by K-fold cross-validation are from one another. The graph indicates a consistent outcome, indicating that the system has been properly trained to recognize sad messages.

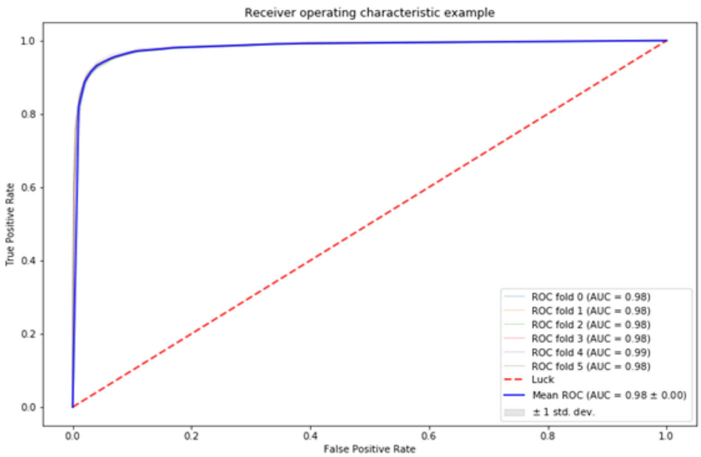

Figure 5. ROC curves with cross-validation

Conclusion

We built many supervised and unsupervised learning techniques in this research. We used the Random Forest with tf-idf vectorization model, and the results were f1-score 95% and ROC-area 0.98. We improved prediction by over 20% when compared to the method we had previously developed. On that dataset, we evaluated an unsupervised model as well, and it unexpectedly produced excellent results.

Future research might go in a number of exciting areas. One of them is using the PyTorch framework to create deep learning models. To stop potential suicide attempts and other self-inflicted harm, the government will develop an alerting system to track people's mental states. We posed a fundamental research issue concerning identifying depressed postings in social media and expressed worry about data anonymity, particularly when the subject is delicate and unclear. We managed the training algorithm's parameters, used the ROC curve to verify it, and displayed the outcomes in two dimensions. We have made it an open-source project to allow for future updates and adjustments.

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