Predicting Depression with Text, Image, and Profile Data from Social Media

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Abstract: In this study, we focused on the task of identifying depressed users based on their digital media on a social network. We processed over 60,000 images, 95,000 posts, and 9,000 subscription items related to 619 user profiles on the VKontakte social media network. Beck Depression Inventory screenings were used to assess the presence of depression among these users and divide them into depression and control groups. We retrieved 6 different text based feature sets, images, and general profile data. The experimental evaluation was designed around using all available data from user profiles and creating a prediction pipeline that can process data samples regardless of the availability of text or image data in the user profile. The best result achieved a 69% F1-score with a stacking classifier approach.

1 INTRODUCTION

Depression can have a severe impact on the quality of life of individuals and it is one of the main causes of disability in the world (WHO, 2017). This mental disorder is closely related to a variety of somatic diseases and cases of self-harm behavior. Not surprisingly, researchers in the field of psychology are making great efforts to study the phenomenon of depression.

Society in its current state is strongly merged with social networks. The popularity of social networks made it possible to study human behavior, personal traits, and mood by mining and analyzing the data provided by users. At the same time, given the fact that depression can affect human behavior, researchers came up with the idea of monitoring depression and other mental disorders by using social media data (De Choudhury et al., 2013a). Analysis of social media data provides an opportunity to privately detect the symptoms of depression before they progress into more advanced stages of depression. This would allow suggesting measures for the prevention of depression and treatment during the early stages.

Our work is based on the general profile data, text messages, and images provided by users from the Russian-speaking social media network VKontakte (VK). We collected screening results of the Beck Depression Inventory questionnaire to perform a binary classification task: predicting whether a user was depressed or not. We already evaluated a similar problem in our previous work (Stankevich et al., 2019), where we analyzed the text from user posts on VK. It was found, that it is not possible to apply the proposed methods for all users since some of them do not have text data in their profiles. The same situation is observed with image data. In contrast to our previous work, we define the depression prediction task as a global task, which means that we include users in our dataset regardless of data types available in their profiles. Overall, we processed over 60,000 photos, 95,000 posts and 9,000 groups of 619 users from VK.

To address this task we formed several feature sets that were based on different data types from user profiles: tf-idf, psycholinguistic markers, objects and color properties of posted images, general profile information, and user subscriptions. To deal with missing data we evaluated several approaches to form feature vectors and used a stacking classifier approach on the data, which yielded the best results on this task.

2 RELATED WORK

There are growing amounts of studies related to the topic of predicting mental health by processing data

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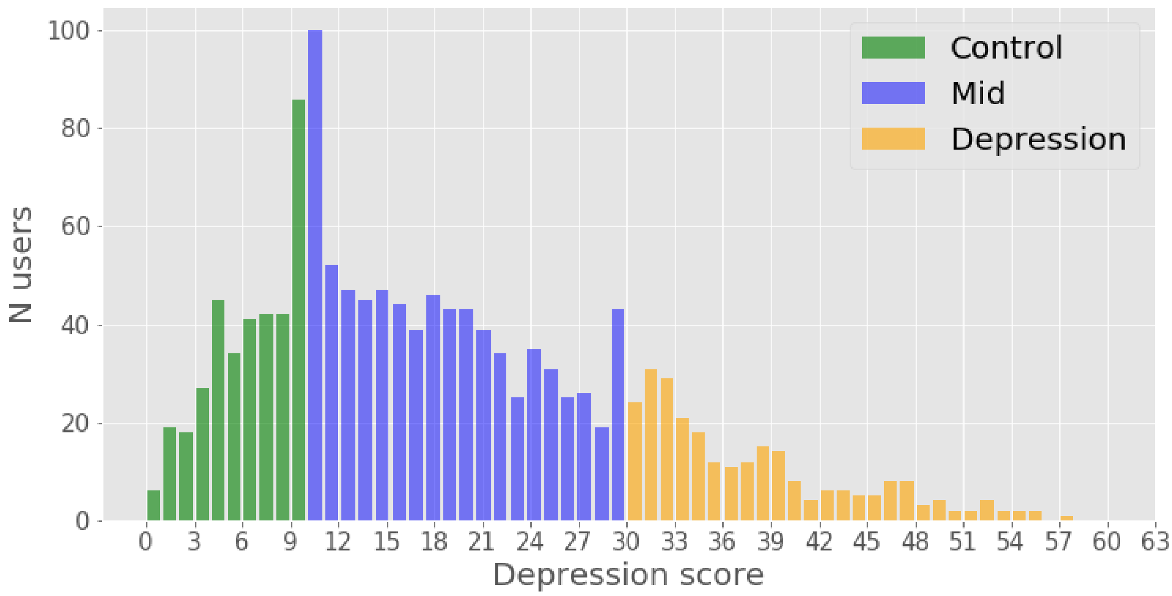

Figure 1: Beck Depression Inventory screening results. Control group: *score⩽10*; Depression group: *score⩾30*.

from social networks, and the majority of them are focused on analyzing text data (Wongkoblap et al., 2017). This is not surprising since the main content of social media usually consists of various user text messages. A good example of text-based analysis is the Clef/eRisk series, that provided a shared task and dataset of Reddit users' messages for researchers to address the task of early risk prediction of depression (Losada et al., 2017; Losada et al., 2018). From this point of view, this problem is closely associated with the problem of predicting mental health from text in general, not only from social media. For example, an interesting task of predicting current and future psychological health from childhood essays was provided by the Clpsych 2018 shared task (Lynn et al., 2018). We should also note the Linguistic Inquiry and Word Count tool (LIWC) (Tausczik and Pennebaker, 2010) - the feature extraction tool, which was successfully utilized in many psychological studies, as well as in studies related to our topic (Wang et al., 2017; Schwartz et al., 2016; De Choudhury et al., 2013b).

The image data posted by social media users can be analyzed by searching for cues of mental disorders. The dataset of 43950 photos from 166 Instagram users was utilized to address the depression prediction task (Reece and Danforth, 2017). Authors of the work retrieved color properties, filter usage, frequency of human faces, and some activity features from Instagram accounts to perform binary classification. In another study, image properties such as color theme, saturation, brightness, color temperature, and color clarity were analyzed to detect psychological stress (Lin et al., 2014a).

In addition to text and image data, it is also possible to retrieve valuable features from general information about users' profiles, activity, and interactions between users and communities in social media. For example, posting time, the number of followers/follows, the number of Twitter reply posts, retweets and links were applied as features for the depression prediction model in (De Choudhury et al., 2013a). There are several works that studied the graph structures of social media interactions to find signs of mental disorders (Wang et al., 2017; Bollen et al., 2011). Another study evaluated the possibility of using the digital media content of Facebook users (Kosinski et al., 2013) to predict personality traits and socio-demographic attributes.

Researchers provide a methodological framework, as an alternative to similar works(Shen et al., 2017; Ghosh and Anwar, 2021; Chiu et al., 2021), which solves the problem of predicting mental health and, in particular, depression, by analyzing records on social networks. However, the majority of the studies evaluate this task by utilizing text, images, and social media activity data separately, and there is a lack of works that predict depression by processing all types of social media data simultaneously.

3 DATASET

To form the dataset, we implemented the Beck Depression Inventory questionnaire (Beck et al., 1996)

Table 1: Available Data in Control and Depression Groups.

Data Type	General Profile	Text	Images	Text + Images
Depression	259	148 (57.1%)	195 (75.2%)	110 (42.4%)
Control	360	239 (66.3%)	238 (66.1%)	156 (43.3%)
Sum	619	387 (62.5%)	433 (69.9%)	266 (42.9%)

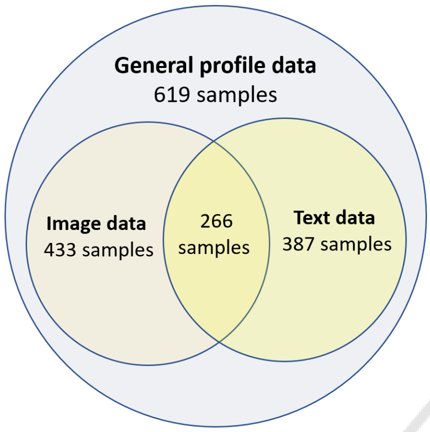

Figure 2: Available data from 619 VK users.

and VK API authorization in our web-application that was specially developed for our task. Using the internal VK advertisement system, we asked volunteers to participate in our research by providing access to their VK data and completing the Beck questionnaire under privacy concerns. There are 1330 VK users who provided Beck screenings and social media recordings. The Beck Depression Inventory is a well-known and well-validated 21-item questionnaire designed to measure the severity and presence of depression on a 0 to 63 score scale. The distribution of depression screening scores is presented in Fig. 1.

The questionnaire scores were used to define 3 groups of users: control group (score$\leqslant$10), middle group(11$\leqslant$score$\leqslant$29), and depression group (score$\geqslant$30). These cut-off values closely correspond to the values presented in (Beck et al., 1988). Similar to our previous work (Stankevich et al., 2019), we removed users with middle scores to perform a binary classification on data. After removing the middle we ended up with a dataset of 619 users. We outline 3 data types that are possible to retrieve from VK:

- General profile data.
- Text data;
- Image data.

All of the 619 users have general profile data, but not every user has images or enough text volume in his/her profile. It seems that some users only use VK as messenger app. The analysis of these profiles revealed that the main activity in their profiles are reposting (analog of retweets from Twitter). The diagram in Fig. 2 provides some insight into how the data partition looks like.

Overall, the dataset includes the data from 387 users who have a sufficient volume of authored text, 433 users who have more than 10 images, and 266 users who had enough text and image data. The statistics about available data between control and depression groups are demonstrated in Table 1.

Data Availability. Unfortunately, there is no complete way to anonymize data that we collected, because that part of VK profiles is freely available on the Internet. That means that it is not possible to provide depression screening results at the same time with raw text and image data without possibly revealing the identity of participants, which is contrary to our privacy concerns agreement with volunteers. However, we can consider sharing already processed data for research purposes under the data agreement form, if we will become sure that there is no way to reveal users' identities using this data. We also provide some code sources for VK data loader[1] and evaluation pipeline[2].

4 FEATURE SETS

4.1 General Profile Data

We outlined two types of features that we were able to retrieve from general profile data. First of all, we retrieved features available on the main page of the profile. There are some quantitative features: the number of friends, followers, messages, affiliations, photos, audio- and video- content, likes on user posts, repost ratio, etc.; categorical features from VK predefined list of information about a person: attitude to alcohol and smoking, the main goal in life, marital status, etc.; binary features that indicate the availability of the following information in profiles: religion, favorite books, films, quotes, games, relationship status, TV, and online shows, etc. We named these features the activity set (**Activity**). In general, people in the

[1] https://github.com/naignatiev/VKParser7
[2] https://github.com/naignatiev/psy_vk

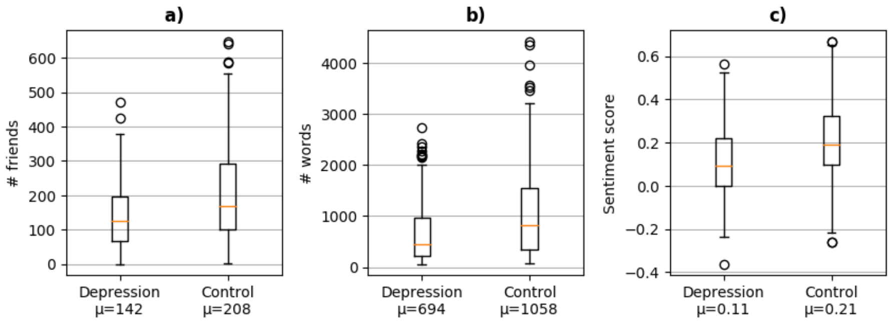

Figure 3: Examples of feature distributions in control and depression groups: **a)** number of friends, **b)** number of words, and **c)** *sentiment score*; μ - mean.

depression group have fewer friends (see *a)* in Figure 3), which is also noted in other studies (Stankevich et al., 2019).

We also considered information about users' subscriptions as general profile data and formed a subscriptions feature set (**Subs.**). We retrieved the list of groups to which every user subscribed to, and gathered information about these groups. Groups with less than four subscriptions from users in our dataset were removed from our feature set. We processed around 9500 subscription items and identified 28 features. The 33- and 66-percentile cut-off values of the total number of group subscribers were used to determine 3 group types: *large, medium, and small*. The most common topics of groups were used to determine 21 types: *humor, creativity, cooking, education, media, city community, show, literature, society, science, design, unspecified type of community, culture, cinema, style, photography, tourism, music, artist, animals, and personal care*. Groups age restrictions were used to describe another 4 types: *0+, 16+, 18+ and not specified*. For each user, we processed their subscription list and counted how many of their groups fall into these 28 categories. The resulting values were normalized by the total number of user subscriptions.

4.2 Text Data

Our text data contains 95255 user messages, where for each user we assembled messages with an overall volume of up to 60000 characters from posts that are most close to the Beck Depression Inventory screening date. Large messages with lengths exceeding 5000 characters were removed from observation since manual analysis revealed that these texts are not authored by users themselves in most cases. Since the procedure for text selection for all users was the same, it can be judged that the users in the depression group generally provide less textual volume on social media (see *b)* in Figure 3). The first text data based feature set is psychological markers (**PM**), which contains a large number of features that have been identified based on the lexical, morphological, syntactic, semantic, and sentiment characteristics of the text (Smirnov et al., 2021). The open access version of markers retrieving tool with limited functionality available at github[3]. The sentiment score of each user was calculated with a help of the Linis-Crowd sentiment dictionary (Koltsova et al., 2016) by summarizing sentiment scores of each word in user messages. Distributions of sentiment scores (normalized by sentence count) in the depression and control groups presented at *c)* in Figure 3. Features from the PM set are similar to the PM set from our previous work (Stankevich et al., 2019), but we also extended it with dictionary based features, which were previously separated from the PM set, and semantic features (Shelmanov and Smirnov, 2014). As a second text-based feature set, we computed tf-idf values over the unigram representation of user messages (**TF-IDF**).

4.3 Image Data

We utilized Faster R-CNN (Ren et al., 2016) pretrained on the COCO (Lin et al., 2014b) dataset to detect 80 types of objects on images from users' profiles. The three image sources that were observed were: avatar (profile pictures), images from messages, and custom user albums. Overall, we processed 61794 user-related images. For each image source, we calculated the frequency of occurrence of each object. The frequency value of each object occurrence was normalized by the total image count on the respective profile (**Objects**). In addition, we retrieved color features (**Colors**) from users' images by computing the average values and standard deviation of each component of the following color spaces: RGB, HSV, XYZ, LAB.

[3] https://github.com/tchewik/titanis-open/

Table 2: Best cross-validation binary F1-scores for depression class.

Classifier	XGB	LGBM	CAT	RF	NB	SVM	KNN	LR	MLP	R
Activity	.62*	.55	.62*	.59	**.63***	.59	.54	.59	.59	
Subs.	.61*	.58	.61*	.56	.58	**.62***	.59	.57	.56	
PM	.56	.50	.57	.55	.61*	.55	.59*	**.63***	.50	
TF-IDF	.57	.53	.57	.54	**.68***	.61*	.59*	.50	.54	
Objects	.54	.50	.55	.53	.59*	**.59***	.58*	.49	.50	.40
Colors	.51	.44	.56	.50	.59*	**.59***	.59*	.56	.45	
1-stack	.66	.65	**.66**	.65	.65	.64	.59	.63	.64	
3-stack	.70	.67	**.71**	.67	.67	.69	.69	.68	.69	
All	.56	.51	.58	.48	.60	**.61**	.45	.57	.54	

* predictions of these classifiers were used to train 3-stack model

Table 3: Classification report on the test data.

Feature set	Model	Depression class			Control class			F1-macro
		Recall	Precision	F1-score	Recall	Precision	F1-score	
Activity	NB	.68	.57	.62	.64	.74	.68	.65
Subs.	SVM	**.70**	.59	.63	.65	**.75**	.70	.67
PM	LR	.67	.55	.60	.60	.72	.65	.63
TF-IDF	NB	.68	.52	.59	.55	.71	.62	.60
Objects	SVM	.67	.53	.59	.57	.70	.63	.61
Colors	SVM	.62	.56	.59	.65	.70	.67	.63
1-stack	CAT	.57	.57	.57	.69	.69	.69	.63
3-stack	CAT	.65	**.63**	**.64**	**.73**	.74	**.74**	**.69**
All	SVM	.56	.56	.56	.69	.69	.69	.62

5 METHOD AND EVALUATION SETUP

Social media contains information about users of different kinds. In our particular case of predicting depression from social media, we analyzed VK data and outlined three types of information about users that we can assemble: general profile data, text data, and image data. Recent studies demonstrate that it is possible to process all of these data sources to retrieve features, which can distinguish depressed and non-depressed users. The problem is that it is not possible to apply prediction models that are trained on text-based features for users that are missing text messages in their profiles. The same is true for image-based prediction models. Taking into account that datasets for this type of research are usually relatively small, It is also hard to strictly compare performance yielded by these models since they are trained on completely different samples. If we observe the situation where we need to run a real world application that predicts the depression status of social media users, it would not be that easy to determine which model we should use. To address this problem we consider the given task as a global task, without separation on the text-based and image-based datasets, and generalize our approach to identifying depressed users. To evaluate the performance of our models we split our data on train and test samples (468 for the train part and 151 for the test part). The diversity of available data was taken into account to make balanced splits.

We build a pre-processing pipeline with the following steps: missing values replacement, feature selection, data transformation, and dimensional reduction. Along with parameters of classifiers, the settings of each of the pre-processing stages were considered as a hyperparameter and were optimized using the Tree-Structured Parzen Estimator approach (Bergstra et al., 2011) with the help of *hyperopt* (Bergstra et al., 2013) on 3 times 5-fold cross-validation. It was found empirically, that three repetitions are enough to not overfit hyperparameters to the training set. At the missing values replacement step, missing data was replaced by a median, average value, or zeros. The k-Best Nearest Neighbor algorithm with varied k-values was used for feature selection. At the stage of transformation, the data were scaled to a normal, standard or Gaussian-like form. As part of pre-processing, PCA with linear, poly or rbf cores was used to lower the number of dimensions. For the tf-idf sparse dimension, we also used truncated SVD for reduction. It is important to note, that each of the pre-processing steps could be skipped.

We evaluated three gradient boosting algorithms: XGBoost (**XGB**) (Chen and Guestrin, 2016), LightGBM (**LGBM**) (Ke et al., 2017), CatBoost (**CAT**) (Prokhorenkova et al., 2017) and 6 classic machine learning algorithms: support vector machine (**SVM**), random forest (**RF**), gaussian naive bayesian classifier (**NB**), k-nearest neighbors (**KNN**), multilayer perceptron (**MLP**), and logistic regression (**LR**). We also included a random based model for comparison (**R**).

To address the proposed idea of treating data from social media users in an equal way regardless of its diversity we utilized the stacking classifiers approach. More specifically, models predictions with the best train scores from each feature set evaluations were used to train the new classification models. We performed this approach with 1 (**1-stack**: 6 features) and 3 (**3-stack**: 18 features) best scores from each feature set. As another evaluation setup, we combined all of the 6 feature sets into one feature space (All) and applied chained equations (Azur et al., 2011) and k-nearest neighbors (Troyanskaya et al., 2001) approaches for missing values imputations (which were also designed as a hyperparameter for optimization).

6 RESULTS

The results of the best cross-validation performances are presented in Table 2. All values in Table 2 represent binary F1-scores for the depression class. The best result for each feature set is highlighted in bold. The results calculated on the test data are presented in Table 3.

Comparing the initial 6 feature sets by F1-score for the depression class, the best scores were achieved by models that were trained on general profile data: .64 with activity and .65 with subscriptions. This result is not surprising since these feature sets were based on information about users that was available for all 619 users. The test scores with text-based feature sets are .60 and .59 with the PM and tf-idf feature sets retrospectively. With image-based features test scores were both around .59. We understand that we are not able to adequately compare performance conducted on the text and image-based sets since classification performance in both situations were distorted by samples with values inserted during the missing values replacement step. However, this step was included to perform a classification stacking approach on the data. Staking predictions with 1-stack has not demonstrated any good results on the test data. But with the 3-stack approach over the CatBoost classifier, we were able to improve results to .64 on the test samples, which is the best result in our experiment. In addition, the 3-stack model demonstrates the best F1-scores for the control class (.74) and F1-macro (.69).

Table 4: Top 5 CatBoost feature importance.

Base Level Model	Feature Importance
CAT: activity	56.6960
KNN: tf-idf	26.4112
XGB: subscriptions	14.1834
SVM: subscriptions	1.4027
LR: PM	1.1157
SVF: tf-idf	0.1907

We retrieved feature importance values of the 3-stack model and demonstrated them in Table 4. It is noteworthy that the predictions obtained from the image data based models were almost completely ignored in this case. We assume that correct predictions with objects and color features are almost completely coincided with predictions given by classifiers trained on text and general profile data features.

Generally speaking, the obtained prediction accuracy is comparable in quality to other studies (Skaik and Inkpen, 2020). However, it should be noted that a direct comparison with other works is impossible, as all depression detection studies were carried out on other social networks, with a different class balance and using different metrics.

7 CONCLUSION

The work describes the depression detection task that was performed on the basis of VK social media data. We formed a dataset that consists of text, image and profile data from personal pages of 619 VK users. The results of the Beck Depression Inventory screenings were used to split our users into depression and control groups in order to try to classify them using machine learning methods. User social media data was processed to retrieve activity, subscriptions, psycholinguistic markers, tf-idf, image objects, and image color properties feature sets. The experimental evaluation was designed around using all available data from users' profiles and creating a prediction pipeline that can process data samples regardless of the availability of text or image data in the user profile. We applied the stacking classifiers technique by combining predictions from the best models that were trained on the different feature sets and used them as features for a meta-classifier. This method allows reaching the best performance in our experiments with around 64% of binary F1-score for depression class and 69% F1-macro.

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