Prediction of Adolescent Suicidal Tendency Based on Random Forest Algorithm

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Abstract. Suicide is a serious public health problem in today's society. It is of great social significance to conduct in-depth research on suicide prevention. In this study, suicide risk assessment methods based on random forest algorithm were investigated. The random matching and traversal matching algorithms are used to optimize the combination of hyperparameters, and the fitting problem of this model in prediction accuracy improvement is improved. Experiments show that the evaluation results of the random forest model are in line with expectations (MSE, RMSE, MAE, MAPE, R-^{2} are good). The results of this study can be applied to the early intervention of suicide prevention. At the same time, it also puts forward the reflection and improvement of the model.

Keywords: Social media · Teenagers · Suicide warning · Machine learning · Random forest prediction

1 Introduction

Social media refers to an emerging online community composed of various discussion forums or websites where members can communicate and interact via the internet. Social media has rapidly developed and is widely present on platforms such as social media, blogs, and forums.

Researchers have made significant progress in studying social media over the past few decades, exploring its formation, development, functions, and impact. Studies have found that social media formation often arises from differences in individuals' common interests, values, or lifestyles (Rheingold, 1993). The development of social media is often influenced by communication and interaction among individuals, as well as social norms and culture within the community (Wellman, Haase, Witte, & Hampton, 2001). The functions of social media are multifaceted, as it can provide individuals with identity recognition, social support, information dissemination, and communication (Kozinets, 2002). The impact of social media is also multifaceted, as it can affect individuals' emotions, behaviors, and attitudes, and have effects on society's culture, politics, and economy (Jones & Fox, 2009). However, the interaction between the impact of social media and other individual and societal factors is not yet clear (Jones & Fox, 2009).

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Social media refers to an online community established through the internet, where members can communicate and interact online. Social media users often disclose their information, emotions, and attitudes in the community, and this behavior is known as "self-disclosure.“ Self-disclosure refers to individuals voluntarily expressing their information, emotions, and attitudes to others in the communication process (Derlega, Metts, Petronio, & Margulis, 1993). Self-disclosure is an important part of interpersonal communication, promoting communication and interaction between individuals, and has positive effects on individuals' emotions and psychological health (Jourard, 1971). In social media, users are often more willing to disclose their information, emotions, and attitudes than in real life (Joinson, 2008). This phenomenon is called the "online disinhibition effect" (Suler, 2004). The online disinhibition effect arises because individuals in the online network often appear more anonymous, abstract, and detached from reality, making it easier for individuals to relax their psychological barriers and disclose more information, emotions, and attitudes (Suler, 2004). Studies have shown that individuals' self-disclosure behavior in the online network can have various effects on their social, psychological, and physical health (Joinson, 2008). For example, self-disclosure in the online network can promote communication and interaction between individuals and enhance social support (Joinson, 2008). Additionally, self-disclosure in the online network can improve individuals' psychological health, such as reducing anxiety and depression (Joinson, 2008). However, excessive self-disclosure can also have negative effects on individuals, such as increasing their self-centeredness and self-satisfaction (Joinson, 2008).

Among social media users, teenagers represent the largest group. According to a report (Smith, 2019), 95% of teenagers (i.e., those aged 13–17) in the United States use social media, and they also spend more time on social media than adults. This means that teenagers have a significant presence on social media. Teenagers typically express themselves on social media by posting, commenting, or sending private messages (Kowalski, Limber, & Agatston, 2008). They often post information on their own pages or on others' pages, as well as make comments in forums, chat rooms, or other social media (Kowalski et al., 2008). The anonymity of expressing oneself on social media gives individuals a sense of security, increases self-disclosure, and allows for the expression of emotions that may be difficult to express in person. It also helps them find like-minded individuals. On the other hand, information overload can lead to self-harm, making emotionally immature teenagers more prone to negative emotions, which they express on social media. Studies have shown that teenagers are willing to express their suicidal tendencies on social media (Eisenberg, Neumark-Sztainer, Story, & Bearinger, 2006). Teen suicide is a serious social and health problem, with thousands of teenagers dying from suicide each year globally (World Health Organization, 2019). In China, teenage suicide has long been a serious social and health issue. According to statistics from the National Health Commission of the People's Republic of China (2017), the suicide rate among Chinese teenagers was 7.6 per 100,000 in 2015, with the suicide rate among male teenagers at 9.3 per 100,000 and that among female teenagers at 5.9 per 100,000. In addition, according to statistics from the China Youth Development Foundation (2018), more than 40,000 Chinese teenagers committed suicide in 2017, accounting for 40% of the total number of suicides in China. Researchers have found that the frequency of suicidal statements by teenagers on social media is higher than that in other places (Eisenberg et al., 2006). Another study also found that many teenagers mention suicide, suicidal tendencies, or suicidal methods on social media (Eisenberg et al., 2006). At the same time, there is a correlation between a teenager's suicidal tendencies expressed on social media and those expressed in real life (Eisenberg et al., 2006). This means that social media may be a valuable channel for crisis intervention and can help identify which teenagers may need help (Eisenberg et al., 2006).

In recent years, machine learning techniques have achieved significant success in identifying whether users' social media posts have suicidal tendencies. Studies have shown that by analyzing user posts on social media through machine learning, it is possible to effectively identify users at risk of suicide, providing strong support for early intervention and prevention of suicide. Machine learning is a branch of artificial intelligence that can automatically make predictions and decisions by analyzing and learning from large amounts of data. Specifically, machine learning techniques can analyze the text of user posts on social media to identify those containing suicidal tendencies. For example, research has shown that through sentiment analysis of Twitter users' posts, users with suicidal tendencies can be effectively identified (Hershkovitz et al., 2017). Additionally, machine learning techniques can analyze language features in user posts on social media to identify those with suicidal tendencies (Lin et al., 2018).

Random forest algorithm is a commonly used machine learning algorithm that can be used to predict mental health. Studies have shown that the random forest algorithm can effectively predict the suicidal tendencies of adolescents on social media (Chiu et al., 2017; Lin et al., 2018; Li et al., 2016). The random forest algorithm has high prediction accuracy and can effectively handle high-dimensional data and nonlinear relationships (Breiman, 2001; Chen & Guestrin, 2016). Additionally, the random forest algorithm has strong generalization ability, meaning it can also perform well in predicting unknown data (Breiman, 2001). In recent years, the use of random forest algorithms in predicting whether social media users have suicidal tendencies has increased. For example, in one study, Gaur et al. (2019) analyzed Twitter data using the random forest algorithm and developed a model to predict whether users have suicidal tendencies. The researchers preprocessed the Twitter data and extracted some features, including users' personal information, post text content, and user interaction information. Then, they used the random forest algorithm to model these features and evaluated the model. The results showed that the model had a high accuracy rate of 78.6% in predicting whether users have suicidal tendencies. Another study used the random forest algorithm to analyze Instagram data to predict whether users have suicidal tendencies (Xu et al., 2018). The researchers extracted some features, including users' personal information, post text content, image features, and user interaction information. They used the random forest algorithm to model these features and evaluated the model. The results showed that the model had a high accuracy rate of 82.3% in predicting whether users have suicidal tendencies. In a study of Chinese social media platforms, Wang et al. (2017) used the random forest algorithm to analyze Weibo data to predict whether users have suicidal tendencies. The researchers extracted some features, including users' personal information, post text content, language features, and user interaction information. They used the random forest algorithm to model these features and evaluated the model. The results showed that

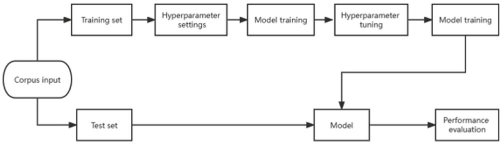

Fig. 1. Experimental Procedure

the model had a high accuracy rate of 80.7% in predicting whether users have suicidal tendencies.

However, at present, there is no machine learning model specifically trained on social media posts of the adolescent population for learning purposes. This study aims to establish a teenage suicide warning system based on the random forest algorithm.

2 Method

2.1 Sampled Data

Since text recognition algorithms are not involved in this study, it is not possible to make predictions based on real-time utterances from social media. In this study, a self-collected dataset was used for training. The data includes 8419 corpora from the Xiaohongshu platform, among which 1749 corpora are labeled with suicide death user groups, and the rest corpora are non-suicide risk corpora.

2.2 Experimental Procedure

The basic flow of this experiment is shown in Fig. 1.

2.3 Setting of Hyperparameters

First, it is necessary to determine the range of each hyperparameter of the random forest model, and then we will determine the final optimal values for each hyperparameter within these ranges. In other words, we first set a very large range for each hyperparameter that needs to be optimized (for example, for the "number of decision trees" hyperparameter, we can set its range to a very large range such as 10 to 5000), and then we will use optimization algorithms to search within each hyperparameter range later.

In this study, we need to determine which hyperparameters to optimize. We chose several important hyperparameters in the random forest algorithm for tuning, including the number of decision trees (n_estimators), maximum depth of decision trees (max_depth), minimum sample separation (i.e. the minimum number of samples required to split a decision tree node) (min_samples_split), minimum number of samples required for a leaf node (min_samples_leaf), maximum number of features to consider when finding the best node split (max_features), and whether to perform random sampling bootstrap, totaling six hyperparameters.

First, establish a random forest model, random_forest_model_test_base, and pass it into RandomizedSearchCV. cv is the number of folds for cross-validation (RandomizedSearchCV evaluates the performance of each combination using cross-validation),

Table 1. Selection of hyperparameters

Key	Type	Size	Value
Max_depth	list	51	[10,20,30,40,50,60,70,80,90,100,…]
Max_features	list	2	[‘auto‘,‘sqrt‘]
Min_samples_leaf	list	4	[1,2,4,8]
Min_samples_split	list	3	[2,5,10]
N_estimators	list	60	[50,100,150,200,250,300,350,400,450,500,…]

Table 2. Random Matching Merit Results

Key	Type	Size	Value
Max_depth	int	1	400
Max_features	str	1	sqrt
Min_samples_leaf	int	1	1
Min_samples_split	int	1	2
N_estimators	int	1	100

Table 3. Optimal hyperparameter matching value

Key	Type	Size	Value
Max_depth	int	1	400
Min_samples_leaf	int	1	13
Min_samples_split	int	1	2
N_estimators	int	1	100

n_jobs and verbose are related to model threading and logging, and random_state is the random seed for random sampling in the random forest.

Next, train random_forest_model_test_random and obtain the best hyperparameter combination, best_hp_now. The number of times the model is trained is the product of n_iter and cv. Using the above code, a total of 1000 runs are required to obtain best_hp_now_1 (the optimal hyperparameter combination).

2.4 Hyperparameter Traversal Matching Preference

Based on RandomizedSearchCV, 200 rounds of random parameter matching and selection were implemented. However, the result at this point is a result obtained after incomplete random traversal, so the optimal combination may not be the global optimal, but

Table 4. Model evaluation result

	MSE	RMSE	MAE	MAPE	R^2
Training set	2538.659	50.385	24.238	51.759	0.995
Cross verification set	8672.718	91.488	28.347	50.725	0.982
Testing set	4052.125	63.656	27.612	50.935	0.989

only a rough optimal range. Therefore, next, based on the randomly obtained optimal matching results, a full combination traversal matching and selection need to be performed.

Traversing matching means selecting several values in the vicinity of the random optimal matching result, and traversing each matching through GridSearchCV to select better final hyperparameter values.

2.5 Model Operation and Evaluation

For the evaluation of the random forest model, this study adopts the method of cross-validation. Cross-validation is an effective model evaluation method that can be used to estimate the performance of a model on unknown data. The cross-validation method usually divides the training data into several parts, with one part used as a validation set and the rest used as a training set. The model is trained on the training set and evaluated on the validation set. This process can be repeated multiple times, with different validation sets used each time, and multiple evaluation results obtained. The average or median of these results can be taken as the final evaluation result of the model. The fitting results of the random forest model after importing the corpus into the optimized hyperparameters are shown in Table 2, and the excellent fitting effect of the model can be observed from the indicators in the table.

3 Discussion

The random forest model obtained in this study has a good fitting effect, but there may be many problems in specific predictions. Although the random forest algorithm has certain advantages in predicting language data, there are still some defects.

The random forest algorithm is not sensitive enough to imbalanced class data. In language data, different categories may have an unequal number of data. For example, the amount of data in some categories may be much smaller than that in other categories. If this imbalanced class situation is not considered when building the random forest model, the model may be biased towards the majority class, leading to a decrease in the accuracy of predicting the minority class. To solve this problem, some methods can be used to balance the categories, such as sampling, weight adjustment, or stratified sampling. The performance of the random forest algorithm in dealing with multi-class problems is not as good as that of a single decision tree. In language data, there may be multi-class situations. For example, some texts may belong to multiple categories. In this case, the performance of the random forest algorithm may not be as good as that of a single decision tree. This is because the basic idea of the random forest algorithm is to improve the accuracy of the model by combining multiple decision trees, but in multi-class problems, each decision tree may only be able to predict one class, so the accuracy of the random forest algorithm may decrease. To solve this problem, some methods can be used to improve the performance of the random forest algorithm in multi-class problems, such as adjusting hyperparameters to control the depth of the tree or using more trees to increase the complexity of the model. In the future, when using the random forest algorithm for language prediction, it is necessary to pay attention to factors such as outliers, imbalanced classes, computational complexity, and multi-class problems, and take corresponding measures to solve these problems.

4 Conclusion

After using hyperparameter random matching optimization and traversal matching optimization to optimize the hyperparameter combination, the random forest model can be used to predict the suicide problems of teenagers in social media.

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