Can We Predict Whether the Secondary School Students Will Engage in Suicidal Behavior?

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Introduction

Motivation

In recent years, the suicide rate among teenagers has continued to increase, which has attrached great attention from governments and society. It was found by the JED foundation organization that 1 in 3 (30.6%) young adults between the ages of 18 and 25 experienced a mental, behavioral, or emotional health issue, 26.9% of teens ages 12-17 have one or more mental, emotional, developmental, or behavioral problems, and 36.7% of high school students reported feelings of sadness or hopelessness in the past year. According to Richmond (2019), suicide has surpassed homicide as the leading cause of death among teenagers over the past decade in the U.S. Therefore, a focus on the prevention of suicide attempts is imperative for both individuals and society. From an economic perspective, lowering suicide rates is equivalent to boosting productivity. In short, suicide among secondary school students is a crucial societal problem that needs to be addressed. This research aims to identify factors that influence suicide among secondary school students and predict the likelihood of teenagers' suicidal attempts with machine learning approaches, thereby helping parents, educators, and policymakers implement early interventions to reduce teen suicide rates.

Research questions

This study is mainly interested in two research questions. First, can we predict whether secondary school students will attempt suicide in advance based on factors including personal circumstances, behaviors, and experiences by machine learning approaches? Second, what factors, including personal circumstances, behaviors, and experiences, predict whether secondary school students will attempt suicide?

Answer to research questions

This research would mainly focus on identifying most significant factors affecting predictions of suicide attempts from a range of potential related factors such as age, gender, sexuality, violence, smoking, alcohol use, drug use, school connections, etc. as well as how they affect attempt suicide. Concerning relevant published papers, it can be found that those influencing factors discussed in the papers have different degrees of correlation with secondary school student's suicide, so this paper also attempts to make predictions based on data and models of the main factors affecting secondary school students' suicides through multiple Machine Learning methods.

Contribution

This research can identify the commonalities that trigger suicide attempts among secondary school students, thereby alerting parents and schools to enhance care and guidance for students in relevant aspects. It can also provide ideas for the educators and governments to formulate relevant regulations and laws for adolescents, whose development has a great impact on the future of the entire world.

Literature reviews

Byeon, K. H., Jee, S. H., et al. (2018) found binge drinking experience and suicide attempts were highly related, binge drinking experience would increase the risk of suicide attempts significantly for both males and females in Korean adolescents. The similarity with this work is the response to suicide attempts and the logistic method applied are the same, and there are several interested factors used to predict the response to suicide attempts. The dissimilarity is that this work would use a much wider range of features other than the only interested one binge drinking experience in this study, also, besides explaining the effects of features, this work also focused on predicting performance.

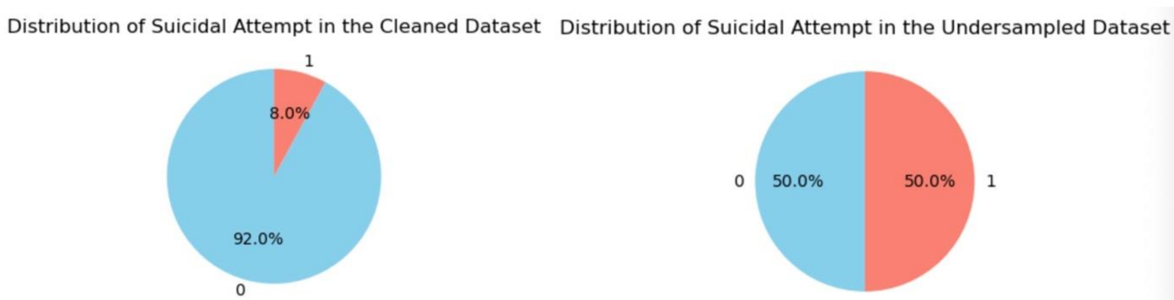
King, R. A., Schwabstone, M., et al. (2001) found there are indeed significant association persisted between suicidal ideation or attempts and poor family environment, low parental monitoring, low youth instrumental competence, sexual activity, recent drunkenness, current smoking, and physical fighting. The similarity with this work is the response to suicide attempts is the same, and there are a range of related features including family environment, parental monitoring, sexual activity, drunkenness, smoking, physical fighting, and so on. The dissimilarity is that this work mainly focuses on whether this research can use related features to predict suicidal ideation and attempts as accurately as possible and once the goal achieved, this research focus on how to protect adolescents from such dangerous thoughts instead of just exploring the relations between the features and the suicidal ideation or attempts.

Shilubane, H. N., Ruiter, R. A., et al. (2013) found feelings of sadness or hopelessness, being the victim or actor in violent acts and illegal substance use contributed significantly to the explanation of suicide ideation and attempt. The similarity with this work is the response suicide attempts and there are a range of related features. The dissimilarity is that this study focused more on the exploring analysis by using description methods such as distribution plots, statistical tests such as t tests, chi-square tests to draw conclusions. However, this work focused on models' results which use all of possible related features at the same time not just pairwise research like using t tests and chi-square tests.

Data and Methodology

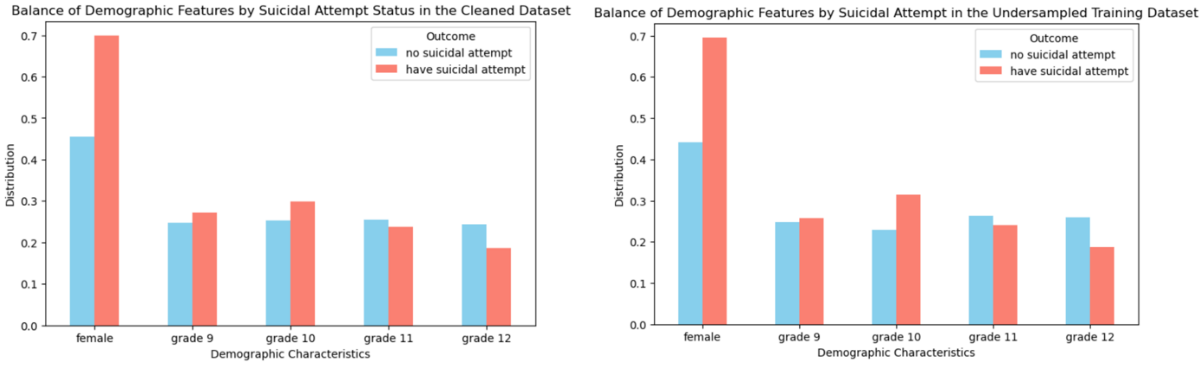
The data for this research comes from the results of the survey conducted by Youth Risk Behavior Surveillance System (YRBSS) in 2021. YRBSS has been monitoring the priority health risk behaviors and experiences that contribute markedly to the leading causes of death, disability, and social problems among adolescents and adults in the United States since 1990. The 2021 survey selected for this paper sampled students in grades 9 to 12 from all public schools, Catholic schools, and other private schools in the U.S.. Because when the answers to questions logically conflict, both answers will be considered invalid missing data, so the data were cleaned to eliminate all samples containing invalid data before actually studying the questions discussed in this research.

Figure1. Distributions of Suicidal Attempt in Different Dataset



This research aims at predicting whether students will actually attempt suicide, so the suicide attempt is set as the outcome of the subsequent models. Moreover, because the distances between each answer of the category data present in the survey are unequal, all relevant data were turned into dummy data in this research. However, as can be seen from Figure 1, in the cleaned data, the proportion of students who actually attempted suicide is too low, accounting for only 8% of the total. If this data were used directly, the model would likely obtain predictions that students would not actually attempt suicide. Therefore, we retained all samples that actually attempted suicide in the cleaned data, and used undersampling to re-randomly select the same number of samples that did not actually attempt suicide from the cleaned data to form the final research dataset to ensure the balance of prediction results in the dataset, so as to make unbiased prediction models.

Figure 2. Balance of Demographic Features by Suicidal Attempt Status in Different Dataset



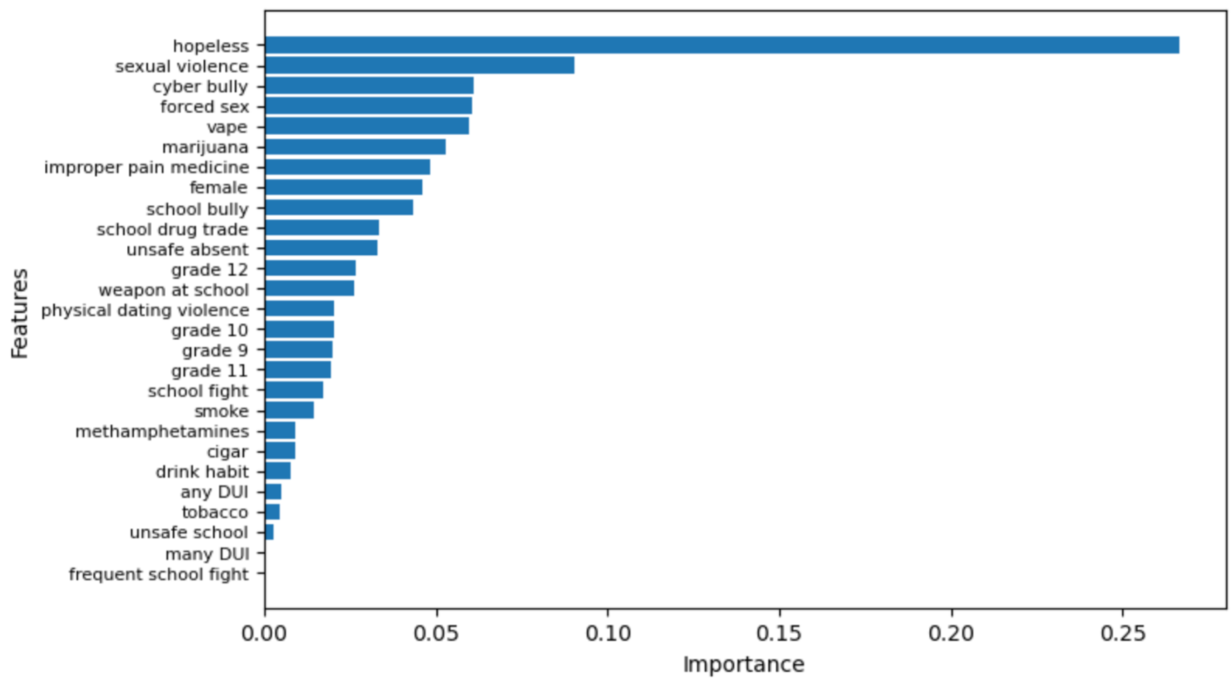
It can be seen from the two histograms in Figure 2 that the proportions of the statistical characteristics of students with different suicide attempt status in the undersampled data are very similar to the proportions of samples in the cleaned dataset, which can illustrate that the undersampled data does not destroy the sample distribution in the original data.

In this research, a total of six methods, including Logistics Regression, Random Forest (RF), Linear Discriminant Analysis (LDA), Decision Tree, K-Nearest Neighbors (KNN), Naïve Bayes are used for modeling, in which the KNN model transforms several different neighbors, and hyperparameter adjustment and cross-validation are performed on the models. In addition to calculating the accuracy of the models, the area under the ROC curves (AUC) of each model is also calculated, and the True Positive Rate (TPR) and False Positive Rate (FPR) of all models are calculated to evaluate the sensitivity and specificity of the model.

Results

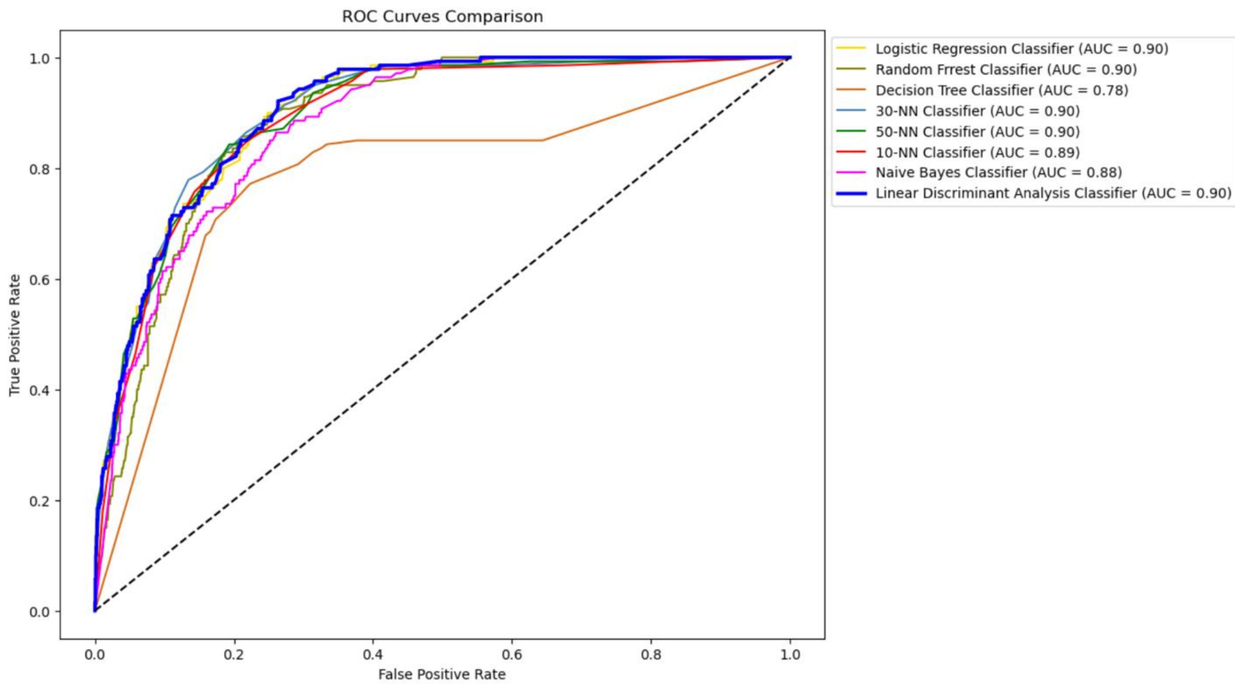
As can be seen from the results of the RF model in Figure 3, there are many factors related to the outcome of students' suicide attempts, but among them, hopeless, sexual violence, and cyber bully are more closely related. This means students are at increased risk of attempting suicide if they have hopeless thoughts, have been victims of sexual violence, or have experienced cyberbullying.

Figure 3. Feature Importance based on Random Forest Model



The ROC curve is a performance measure for classification problems under various threshold settings. As can be seen from Figure 4, except for the decision tree model, the trends of the ROC curves of other models are very similar. Combining Table 1, it can be found that, except for the decision tree model, the AUC values of other models are very high, which means that these models all have good separability measures, that is, these models have good performance in distinguishing whether students have attempted suicide. At the same time, the TPR reflects the sensitivity of the model, and FPR is 1 minus specificity, and sensitivity and specificity are inversely proportional. Therefore, when sensitivity increases, specificity decreases, and FPR increases, and vice versa. More positive values are obtained when the threshold is lowered, thus increasing sensitivity and decreasing specificity. Because the purpose of this research is to reduce student suicide mortality by accurately predicting whether students actually attempt suicide and the factors that influence their suicide behavior, the higher the sensitivity, the better in this research, combining the results of AUC and TPR, LDA is the most suitable model for this research.

Figure 4. ROC Curves for All Models



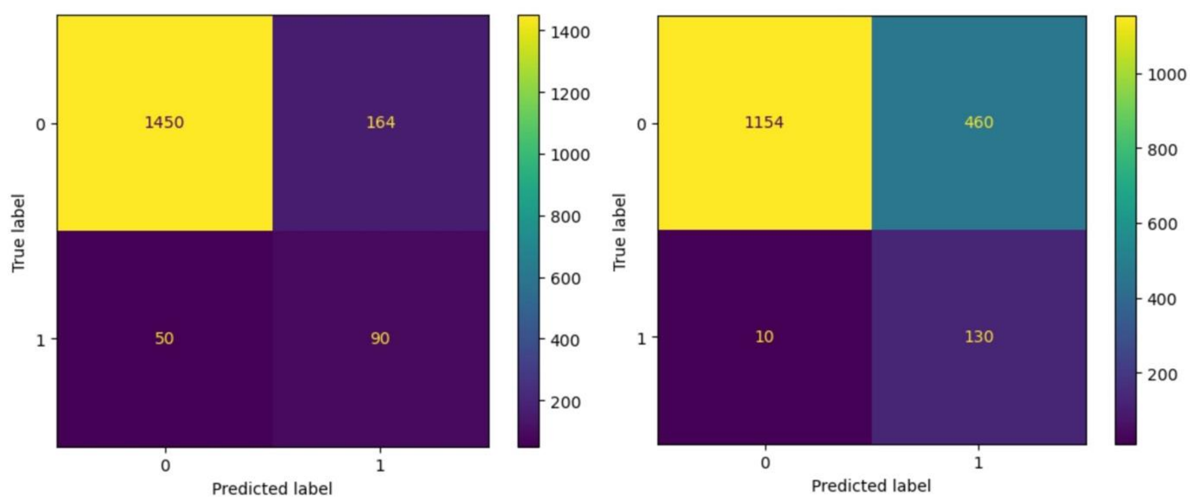
The LDA's accuracy rate of 0.732 suggests that, among 100 teenagers randomly selected from a larger group without preference, the LDA model is capable of correctly predicting the actual condition of 73 individuals. Meanwhile, its TPR of 0.929 indicates that, among 100 teenagers who have attempted suicide, we can successfully predict that 93 of them have actually attempted suicide.

Table 1. Relative Values for All Models

	Accuracy Rate	Tuned 3-Fold CV	AUC	TPR	FPR
50-NN classifier	0.877993	0.759857	0.897263	0.642857	0.101611
30-NN classifier	0.872292	0.767921	0.902846	0.728571	0.115242
Naive Bayes classifier	0.867731	0.684588	0.879308	0.621429	0.110905
10-NN classifier	0.848917	0.769713	0.891664	0.757143	0.143123
Decision tree classifier	0.802166	0.771505	0.782187	0.692857	0.190211
Random forest classifier	0.800456	0.793907	0.886137	0.850000	0.208798
Logistic classifier:	0.769669	0.796595	0.903445	0.871429	0.239157
Linear disriminant analysis	0.732041	0.809140	0.903976	0.928571	0.285006

From Table 1, it can be also found that there is a big gap between the accuracy of the original and after tuning. Through tuning, models can be adjusted to avoid overfitting (where the model is too complex and learns the noise in the training data) and underfitting (where the model is too simple to learn the underlying pattern). A well-tuned model strikes a balance, generalizing well to new, unseen data.

Figure 5. Confusion Matrixes for 50-NN Classifier (Left) and Linear Discriminant Analysis (Right)



As shown in Figure 5, the confusion matrices display the overall performance of the classifiers on the test dataset.

Conclusion

The classification model ultimately selected for this research is LDA, which exhibits the highest TPR, indicating superior sensitivity in detecting potential suicidal tendencies. The low accuracy rate due to the severe class imbalance, with only 8% of the respondents having attempted suicide, means that we should focus on the confusion matrix and the TPR score when selecting the model that best fits the context. By comparing the confusion matrices (Figure 5), it is evident that the LDA model successfully predicted 130 out of 140 students with suicidal attempts, while the KNN model, with fifty neighbours, only correctly predicted 90 students. This discrepancy suggests that the LDA model can potentially save 40 more lives, followed by immediate suicide intervention, resulting in a significant advancement towards our primary goal of detecting any potential suicidal signals.

Following the identification of suicidal tendencies, it is imperative to provide essential tools and support to mitigate students' suicidal thoughts. An analysis of the relevance importance graph highlights that hopelessness holds the highest predictive power among all features. In descending order of relevance, experiences such as sexual violence and forced sexual intercourse also play a pivotal role in predicting suicide attempts. These results bring us the insight that care from their families and school faculties is insufficient to address their traumatized situation. Still, educators and policymakers should also take their role in safeguarding this vulnerable population. For instance, policymakers should consider ways to enhance their protection of adolescents from violent crimes. Simultaneously, parental intervention and comprehensive school education are imperative in preventing risky behaviours such as marijuana use, vaping, and misuse of pain medication, all of which are strongly associated with suicidal attempts.

Despite the valuable result of the model's high sensitivity in detecting suicidal tendencies, there is a main constraint on the model's efficiency in general prediction. The high FPR suggests that the LDA model is incapable of predicting encountering people without suicidal attempts. The elevated FPR implies that the LDA model struggles to differentiate individuals without suicidal tendencies. To enhance the model's overall performance in future studies, reducing the FPR is crucial. This can be achieved by employing a more representative dataset characterized by better demographic balance and evenly distributed outcome classes, effectively mitigating underfitting issues. Additionally, the inclusion of comprehensive risk behaviours as predictors will enable policymakers to formulate more effective regulations and interventions. However, it's essential to acknowledge the uncertainty and limitations in studying this serious topic, as survey data cannot capture the conditions of teenagers who have died by suicide.

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