Using Machine Learning Classification Methods to Predict Suicide Risk of National Taiwan Suicide Prevention Hotlines Callers

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May 2 2019

Abstract

Suicide hotlines is an important prevention tool in reaching people with suicide ideation. The Taiwanese government established National Suicide Prevention Hotlines (TNSPH) in 2009 to reduce the country's suicide rate. Each year, TNSPH received around 70,000 phone calls. Volunteers must evaluate the suicide risk of the callers, but about 60% of callers cannot be assessed due to limited background information and call time duration. This research uses several machine learning classification methods to predict the risk of suicide from this unknown group from the characteristics of known suicide risk groups. Since the TNSPH data is exceptionally imbalanced, the prediction may dangerously bias results toward to the majority group (no suicide risk or low suicide risk). To overcome the issue, several sampling methods were used to balance the data and try to improve model performance. These methods include the Simple Random Sampling and Synthetic Minority Over-sampling Technique (SMOTE). The SMOTE Random Forest Multinomial Model was selected as the best model because of its significant improvement on the false negative rate of suicide risk groups and avoidance of the overfitting issue. This process will effectively identify individuals at high-risk of suicide, allowing TNSPH volunteers to prioritize contacting them, saving countless lives.

keywords: suicide risk, imbalanced data, synthetic sample

1 Introduction

Suicide is recognized as a severe public health concern with nearly 800,000 deaths worldwide annually (World Health Organization, 2018). In other words, one person dies from suicide every 40 seconds. Suicide is not only a significant cause of premature mortality, but it also impacts seven to ten people close to each deceased (Christopher Lukas, 2007). In Taiwan, the issue of suicide has worsened in the last three decades, and the standardized suicide rate had risen from 7.4 per 100,000 in 1990 to 12.5 per 100,000 in 2017. In Taiwan, suicide not only leads to approximately 3,700 deaths per year but it is also the 11th leading cause of all deaths (Taiwan, Ministry of Health and Welfare, 2019).

Telephone crisis hotlines lead to significant decreases in suicides, and are an important tool in reaching individuals with suicidal ideation (Covington and Hovan, 2011). A major goal of hotlines is to respond to callers' short-term emotional volatility by providing immediate support regardless of time or location (Woodward and Wyllie, 2016). Those with suicidal ideation frequently experience psychological and physical disturbances, including depression, post-traumatic stress, social stigma, physical disorders, and heightened suicide risk (Christopher Lukas, 2007).

Taiwanese government established National Suicide Prevention Hotlines (TNSPH) in 2009 to reduce the country's suicide rate.TNSPH provide telephone counseling and crisis intervention with toll-free 24/7 services. Inside the TNSPH, there are approximately two hundred trained volunteers to answer the phone calls. The number of people in mental distress who have the will to contact TNSPH keeps growing. TNSPH responds each year to approximately 70,000 callers; around 15% of these callers are determined to be at risk for suicide (Shaw and Chiang, 2019). The annual call rates and estimated suicidal risk rates are summarized in the below chart. In 2017, the record showed that the total number of telephone calls reached 76,511, which means approximately 325 per 100,000 Taiwanese utilized the TNSPH. Among the 76,511 calls, 11,590 (15.15%) callers were evaluated to be at risk for suicide.

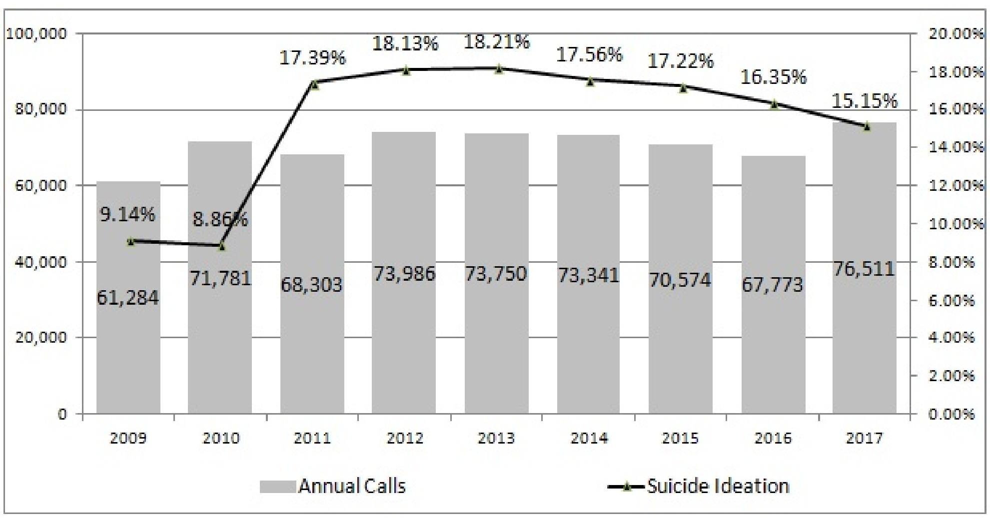

Figure 1: TNSPH Annual Phone Calls

2 Objectives

Based on the level of suicidal risk, TNSPH divides callers into six groups consisting of: (i) no suicide risk (NSR), (ii) low suicide risk (LSR), (iii) moderate suicide risk (MSR), (iv) high suicide risk (HSR), and (v) imminent suicide risk (ISR), and provide them with different strategies and resources. Those not at risk for suicide are treated by one-time counseling, those with low-high suicide risk receive follow-up calls or a referral to psychiatric institutes, and those at imminent risk for suicide receive 911 support.

Besides these five groups, there also exists a fraction of people whose suicide risk cannot be evaluated (Group vi, CANTE). Based on Table 1, it shows that the fraction individuals whose risk cannot be assessed is 65.90%, which is larger than the other five groups (i-v) combined. Table 1 summarizes the 2013 TNSPH suicide risk assessment result.

Table 1: 2013 TNSPH Suicide Risk Assessment Result

Gruop	2013 TNSPH Suicide Risk Assessment	Abbreviation	Phone Calls	%
i	No Suicide Risk	NSR	11,716	15.89%
ii	Low Suicide Risk	LSR	8,540	11.58%
iii	Moderate Suicide Risk	MSR	3,790	5.14%
iv	High Suicide Risk	HSR	511	0.69%
v	Imminent Suicide Risk	ISR	591	0.80%
vi	Cannot Evaluate	CANTE	48,602	65.90%
	Total		73,750	100%

Assessing suicide risk is a difficult task for the volunteers working in TNSPH. The TNSPH 2019 annual report found that the situation is made worse by the anonymity of callers, and around 20% are first-time callers, so volunteers often lack necessary information to make an informed assessment. Each time when a volunteer receives a phone call, their priority is to evaluate the suicide risk and prevent those at imminent risk for suicide from carrying out their plans (TNSPH, 2019).

However, the time is often too short to finish the comprehensive assessment. On average, each phone call duration is only around 10 minutes. During the period of the communication time, the TNSPH has to collect much information, including demographic, socioeconomic, and clinical characteristics, the primary concern for the phone call, and record of previous suicide attempts, to assess the level of suicide risk. Even though volunteers receive at least 200 training hours to help identify the signs of suicide, the volunteers still have little background information to evaluate suicide risk if the caller is unable or unwilling to express suicidal intent (Hunt el. 2018). As a result, usually more than 60% of phone calls fail to assess suicide risk (TNSPH, 2019).

The accurate identification of suicide risk for Group vi (CANTE) is critical because we must prevent any possible suicide attempts from happening by providing them with immediate help. The objective of this research is to apply machine learning classification methods to help predict the suicide risk among Group vi (CANTE). The following sections will demonstrate the methodology and data analysis result.

3 Dataset

We will use the caller data which was collected by TNSPH in 2013. The total sample size of the data is 73,750 with 23 variables. These variables are categorized by demographic, socioeconomic, and clinical characteristics, suicide risk related factors, and call information. Figure 2 demonstrates the structure of all the variables. In our classification model, we define the outcome variable as Y = the result of suicide risk evaluated by TNSPH volunteers during the phone call. The outcome variable has six levels, including NSR, LSR, MSR, HSR, ISR, and CANTE groups.

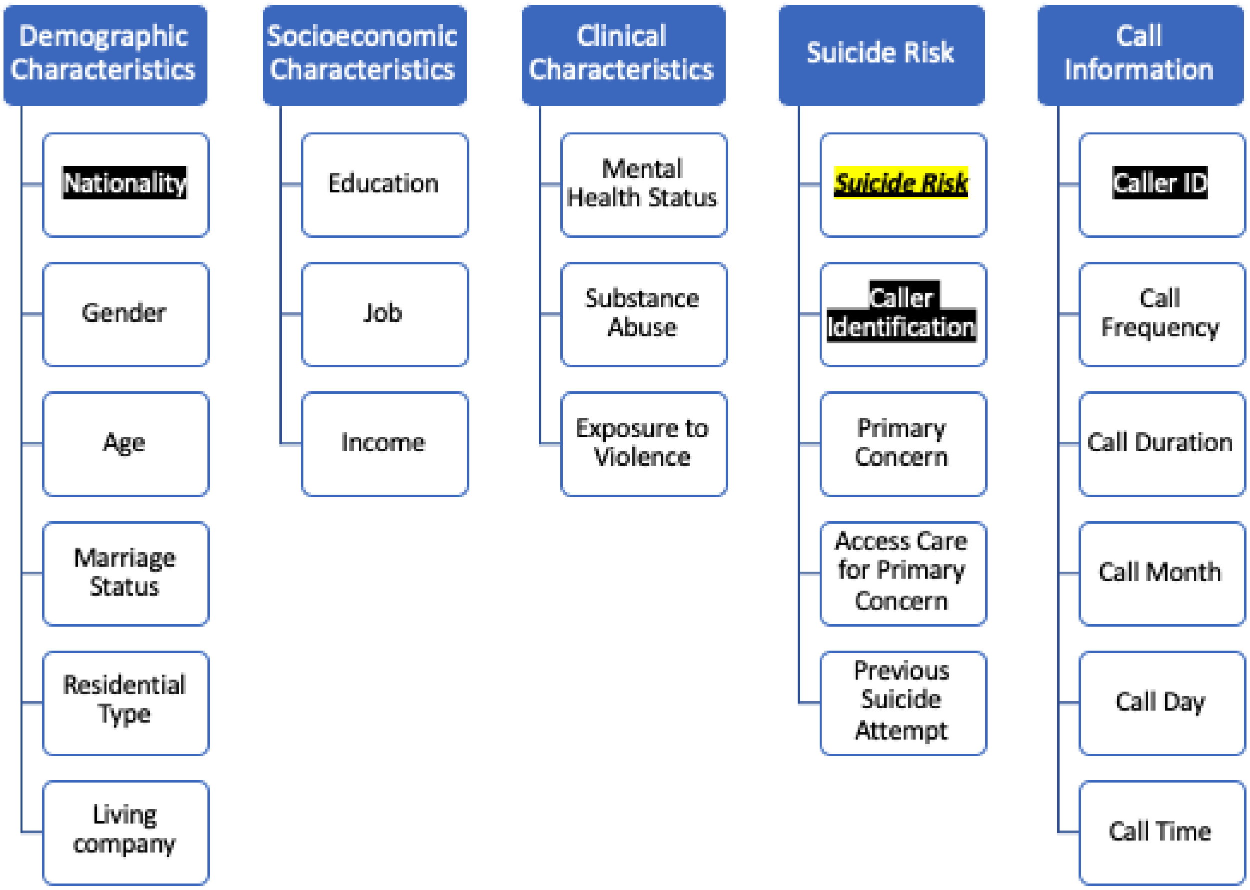

Figure 2: Dataset Structure

To narrow down the scope of the current investigation, we will not analyze the entire dataset; instead, we only focus on specific cases which are obtained by employing the following filtering criteria in Table 2.

Step 1. Refine Research Population: 1) remove non-Taiwanese nationals and those calling on behalf of someone else to report an ISR or a suspected high suicide risk case. After removing the two types of cases, we can remove the variables Nationality and Caller Identification in the dataset because these become only one level that lead to no analytic effect to our prediction model. 2) remove ID variable - this variable is not for analysis use. In summary, we remove three variables from the dataset. Now, the remaining number of predictors is $23 - 1 - 3 = 19$.

Step 2. Clean the Data: 1) remove ineligible phone calls, including informational calls, referral calls, obscene calls, and prank calls. 2) remove cases with call duration of less than 1 minute since these extremely short calls might contain too little information to predict suicide risk.

Step 3. Perform Complete Analysis: most machine learning classification methods cannot deal with missing values. As a result, we have to remove all the observations with at least one missing value.

Step 4. Remove Suicide Risk Cannot be Evaluated Group (CANTE): The research objective of the final dataset is to use the known suicide risk groups (NSR/LSR/MSR/HSR/ISR) to construct the best model for the prediction of suicide risk among the unknown suicide risk group (CANTE). Hence, we have to remove the CANTE group from the dataset.

After completing the data filtering criteria, 5966 inputs remain. Now, the levels of the outcome variable Y = ”suicide risk assessment result” only have 5 levels, including NSR, LSR, MSR, HSR, and ISR. To find the best model, we may collapse LSR/MSR/HSR/ISR variables into one group as ”having suicide risk,” effectively separating the

Table 2: Data Refine Process

		Remove Sample Size	Final Sample Size
Step0	Original Data Set	0	73,050
Step1	Refine Research Population	984	72,066
Step2	Data Clean: remove ineligible calls	15,714	56,352
Step3	Complete Analysis	40,583	15,769
Step4	Remove Suicide Risk Cannot be Evaluated Group	9,803	5,966

outcome Y into 2 levels: no suicide risk callers and having suicide risk callers. After doing this, in the following analysis, we will apply the specific machine learning classification methods both for binary outcomes (2-level) and multinomial outcomes (5-levels).

The variable names and labels of the 19 predictors are recorded in Figure 3. In each predictor, if the sample size in a specific category is too small or cannot not directly help analysis, we will combine the categories. For example, Wenz (1977) mentions that callers have higher suicide risk in the winter. Since the predictor Call Month originally consists of 12 levels (January to December), and these levels cannot help to identify the seasonal effect on suicide risk, we transform the variable into 4 levels (Spring/Summer/Fall/Winter). Another example is the predictor Call Time. Valtonen et al. (2006) discuss the time pattern of attempted suicide. As a result, we transfer the variable from 24 hours levels to 3 levels (day shift/night shift/graveyard shift). Doing so can help observe the effects of call time on suicide risk.

Variable Group	# of Predictors	Variable Name	Variable Lable	Variable Tyoe	Factor Level	Original Factor Level
Outcome		suci_want	Suicide Risk Assement Result	Factor	5 or 2	5 or 2
Demographic Characteristics	1	gender	Gender	Factor	2	2
	2	age	Age	Factor	6	80
	3	marriage	Marriage Status	Factor	5	6
	4	location	Residential Type	Factor	2	23
	5	living_stat	Living company	Factor	3	3
Socioeconomic Characteristics	6	education	Education	Factor	6	6
	7	job	Job	Factor	9	12
	8	revenue	Income	Factor	4	5
Clinical Characteristics	9	mind_stat	Mental Health Status	Factor	3	3
	10	obj_abuse	Substance Abuse	Factor	4	4
	11	viol_stat	Exposure to Violence	Factor	4	4
Suicide Risk	12	main_question	Primary Concern	Factor	13	19
	13	medical_stat	Access Care for Primary Concern	Factor	4	4
	14	suci_record	Previous Suicide Attempt	Factor	2	2
Call Information	15	case_count	Call Frequency	Factor	2	3
	16	rece_total	Call Duration	Factor	3	122
	17	rece_month	Call Month	Factor	4	12
	18	rece_day	Call Day	Factor	7	31
	19	rece_hour	Call Time	Factor	3	24

Figure 3: Predictors Information

4 Methodology

The analysis consists of two parts. The first part is the construction of the possible good models that can be applied for our suicide risk study. The second part pertains to improving the constructed models for the isolation of the best model.

4.1 Find the Best Prediction Model

4.1.1 Construct the Validation Dataset

We will apply machine learning classification methods to find the best prediction model. Due to the research time limit and the data complexity, we use the 80%-20% validation method to evaluate the testing error, instead of the 5-fold Cross-Validation method. As a result, the sample size of the original dataset is 5966, and the sample size of the training and testing dataset is 4773 and 1193, respectively.

To further examine the distribution of the suicide risk outcome, we found a potential issue in the dataset. Most of the callers are evaluated as NSR(48.04%) or LSR(32.79%), while the total proportion of the HSR and ISR group only occupies 3.44%. Here we define NSR/LSR are the majority groups and HSR/ISR are the minority groups. In other words, the distribution of the suicide risk group is exceptionally imbalanced. If we perform Simple Random Sampling to separate the training dataset and testing dataset, there is always a chance we may distort the outcome distribution which then affects the following analyses.

To avoid the Simple Random Sampling issue in our validation dataset, we have to perform Stratified Random Sampling, and assign the stratum as suicide risk outcome. Figure 4 reveals the Stratified Random Sampling results. We confirm the suicide risk distribution in the training dataset and test dataset are both identical to the original dataset. To choose the best machine learning classification methods, we create 100 set of training dataset and testing dataset by simulation with setting up different random seed.

Dataset	Frequency	Multinomial Outcome					Binary Outcome		Total
		NSR	LSR	MSR	HSR	ISR	No Suicide	Suicide	
Original	#	2866	1956	939	97	108	2866	3100	5966
	%	48.04%	32.79%	15.74%	1.63%	1.81%	48.04%	51.96%	100.00%
Train	#	2293	1565	751	78	86	2293	2480	4773
	%	48.45%	33.07%	15.87%	1.65%	1.82%	48.45%	52.40%	80.00%
Test	#	573	391	188	19	22	573	620	1193
	%	48.03%	32.77%	15.76%	1.59%	1.84%	48.03%	51.97%	20.00%

Figure 4: Construct Training/Testing Dataset by Stratified Random Sampling

4.1.2 Machine Learning Classification Methods

We will apply eight machine learning classification methods to construct possible prediction models. These models include the concepts of Naïve Beyes, Logistic Regression/Multinomial Regression, Decision Tree, Random Forest, Bagging, and Boosting. Since we experiment with the binary outcome and multinomial outcome of suicide risk assessment, we output $8X2 = 16$ possible models. Besides, Bagging, Random Forest, and Boosting are related to the concept of Bootstraps, the number of Bootstraps will be assigned a number of 500.

We examine all the possible models and calculate the confusion matrix. To decide the best model, first we will choose the best machine learning classification method by the lowest average testing error. Second, we try to improve the best method if needed. Finally, the best model will be determined by the most significant improvement in the false negative rate of the high suicide risk groups (MSR/HSR/ISR).

4.2 Predict CANTE group

After deciding the best model, we could apply this model to the CANTE group who lack a comprehensive suicide risk assessment to make the appropriate prediction of suicide risk for this group.

5 Data Analysis

5.1 Exploratory Data Analysis

We produce the detailed contingency tables in Figure 16-18 in the appendix to explore the relationship between suicide risk and each predictor. Most of the predictors have significant effects on suicide risk (the p-Values of the chi-square independence test are all close to 0.000).

Here, we identify the essential characteristics of high suicide risk from the information in the contingency tables. If the predictor effect increases as suicide risk increases for groups with larger sample sizes, we will consider that the predictor does affect the suicide risk. To have a better subjective observation, we only focus on the effects of the NSR/LSR/MSR/HSR groups. We do not specifically observe the effects on the ISR group because research findings support that the behavior of the ISR group is notably different from other suicide risk groups (LSR/MSR/HSR).

To summarize, the subjective characteristics of people who have suicide risk are included in the following index. We list the the information about the relationship in Figure 5.

1. Male, 50-59 years old, Divorced/Widowed, Living in Countryside
2. Low Education Level, Unemployed
3. Mental Illness, Substance Addiction, Perpetrator of Abuse, Previous Suicide Attempt
4. Call Duration more than 40 minutes, Call in Winter or Night Hours(15-23PM)

		Suicide Risk Assement Result											
		NSR	LSR	MSR	HSR	ISR	TTL	NSR	LSR	MSR	HSR	ISR	TTL
	Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	2866	1956	939	97	108	5966
Gender	1.Male	31.5%	39.5%	42.7%	63.9%	60.2%	36.9%	903	773	401	62	65	2204
Age	5. 50-59 y	14.0%	16.0%	19.5%	24.7%	37.0%	16.1%	400	313	183	24	40	960
Marriage Status	4.Divorced	21.5%	25.5%	26.2%	32.0%	23.1%	23.8%	617	499	246	31	25	1418
	5.Widowed	2.7%	5.7%	6.4%	5.2%	28.7%	4.8%	78	111	60	5	31	285
Residential Type	2.Countryside	50.8%	46.9%	45.9%	55.7%	63.9%	49.1%	1457	917	431	54	69	2928
Education	1.Primary School	2.3%	5.1%	5.2%	18.6%	5.6%	4.0%	67	99	49	18	6	239
	2.Junior High School	14.2%	18.6%	22.9%	22.7%	16.7%	17.2%	406	363	215	22	18	1024
	3.Senior High School	38.8%	38.5%	40.9%	42.3%	62.0%	39.5%	1111	753	384	41	67	2356
Job	9.Unemployed	43.5%	51.3%	55.7%	66.0%	69.4%	48.8%	1246	1004	523	64	75	2912
Mental Health Status	2.Mental Illness	79.7%	84.8%	87.5%	86.6%	92.6%	82.9%	2283	1658	822	84	100	4947
Substance Abuse	2.Alcohol Addiction	10.9%	17.4%	23.1%	29.9%	25.9%	15.5%	311	341	217	29	28	926
	3.Medicine Addiction	5.2%	10.1%	14.4%	17.5%	38.0%	9.1%	150	197	135	17	41	540
	4.Drug Addiction	2.1%	3.3%	5.1%	11.3%	2.8%	3.1%	60	65	48	11	3	187
Exposure to Violence	2.Abuser	6.7%	10.6%	13.3%	26.8%	34.3%	9.8%	192	207	125	26	37	587
Primary Concern	5.Mental Health Issues	24.6%	30.4%	31.4%	40.2%	33.3%	28.0%	705	594	295	39	36	1669
	10.Unemployment Issue	3.1%	5.8%	4.7%	11.3%	10.2%	4.5%	88	113	44	11	11	267
Previous Suicide Attempt	2.Yes	50.9%	73.1%	83.7%	87.6%	93.5%	64.7%	1460	1430	786	85	101	3862
Call Duration	3.Call duration more than 40mins	5.4%	8.3%	15.8%	21.6%	13.9%	8.4%	155	162	148	21	15	501
Call Month	4.Winter	26.0%	20.8%	22.4%	28.9%	14.8%	23.6%	745	407	210	28	16	1406
Call Time	2.Night Shift	34.2%	46.3%	45.3%	46.4%	44.4%	40.3%	981	905	425	45	48	2404

Figure 5: The Characteristics of High Suicide Risk Group

5.2 Machine Learning Classification Models

5.2.1 Model Performance

We apply eight machine learning classification methods to binary and multinomial outcomes. After 100 simulations, the average testing error for each model is summarized in Table 3. Figure 19-23 in the appendix are the simulated results of each model, including the confusion matrix, testing error, and the false negative rate of each suicide risk group. Here we have three findings:

1. The binary outcome models outperform the multinomial outcome models. The average testing error of the eight classification methods in the binary setting is only around 31.63%, while the average testing error achieves 47.09% in the multinomial outcome. This also implies that the testing error can be improved by at least 15% if we reduce the number of outcome groups from 5 to 2.

2. Random Forest, Boosting, and Bagging serve as the TOP 3 best classification models for both binary and multinomial outcomes. After 100 simulations, the average testing error in binary outcome is 28.03%, 29.07%, and 30.03%, and the average testing error in multinomial outcome is 44.20%, 45.93%, and 45.94%. In the following analysis, we will focus on these three specific methods.

Table 3: Average Testing Error

#	Classification Method	Binary Outcome	Multinomial Outcome
1	Naive Bayes	32.93%	49.05%
2	Naive Bayes + Bagging	32.95%	48.91%
3	Logistic /Multinomial Regression	31.76%	46.72%
4	Logistic /Multinomial Regression + Bagging	31.88%	46.76%
5	Decision Tree	36.35%	49.21%
6	Bagging (mtry=19)	30.03%	45.93%
7	Random Forest (mtry=4)	28.03%	44.20%
8	Boosting (Interaction=3)	29.07%	45.94%
	Average Testing Error	31.63%	47.09%

3. Using multinomial model is our priority because we would like to predict the level of suicide risk and make a more compelling call task for the high suicide risk callers. Figure 6 summarized the 100 times of simulations result for the Random Forest Multinomial Model. The average false negative rate of high suicide risk groups (MSR/HSR/ISR) is notably high (77.09%/99.11%/90.36%). Bagging and Boosting also show a similar trend. As a result, we will further explore how to reduce the false negative rate for constructing the best model. In other words, we have to improve the existing model and find a better model to provide a lower false negative rate for the high suicide risk groups (MSR/HSR/ISR).

7.Random Forest															
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	450.19	178.20	54.28	4.30	6.15	693.12	Predict	NSR	65%	26%	8%	1%	1%	100%
	LSR	102.39	170.09	88.41	9.32	8.44	378.65		LSR	27%	45%	23%	2%	2%	100%
	MSR	19.10	39.72	43.07	4.56	5.10	111.55		MSR	17%	36%	39%	4%	5%	100%
	HSR	0.22	1.04	0.63	0.17	0.19	2.25		HSR	10%	46%	28%	8%	8%	100%
	ISR	1.10	1.95	1.61	0.65	2.12	7.43		ISR	15%	26%	22%	9%	29%	100%
	TTL	573.00	391.00	188.00	19.00	22.00	1193.00		TTL	48%	33%	16%	2%	2%	100%
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	38%	15%	5%	0%	1%	58%	Predict	NSR	79%	46%	29%	23%	28%	58%
	LSR	9%	14%	7%	1%	1%	32%		LSR	18%	44%	47%	49%	38%	32%
	MSR	2%	3%	4%	0%	0%	9%		MSR	3%	10%	23%	24%	23%	9%
	HSR	0%	0%	0%	0%	0%	0%		HSR	0%	0%	0%	1%	1%	0%
	ISR	0%	0%	0%	0%	0%	1%		ISR	0%	0%	1%	3%	10%	1%
	TTL	48%	33%	16%	2%	2%	100%		TTL	100%	100%	100%	100%	100%	100%
Testing Error		44.20%		Sen	34.75%	Spe	78.57%	FP/FN		21.43%	56.50%	77.09%	99.11%	90.36%	65.25%

Figure 6: The Random Forest Multinomial Model

5.2.2 Increase the Numbers of Bootstraps

Now, we discuss several possible solutions to reduce the testing error and the false negative rate. First, we try to increase the number of Bootstraps since our Top 3 classification models, Random Forest, Bagging, and Boosting are all related to the implementation of Bootstrapping. The testing error is possibly improved by increasing the number of Bootstraps. In the previous result, the number of Bootstraps for the three methods is assigned to the baseline, 500. Next, we try to increase the number of Bootstraps to reduce the testing error. We changed the number of Bootstraps from 500 to 5000 and observed the effect on the testing error. The result is summarized in Figure 7. Unfortunately, the strategy fails in both binary and multinomial settings because the testing error remains on the same scale. Imbalanced data in the multinomial setting might be the culprit for this failure. In the next section, we discuss the imbalance issue and the possible solutions while dealing with machine learning classification methods.

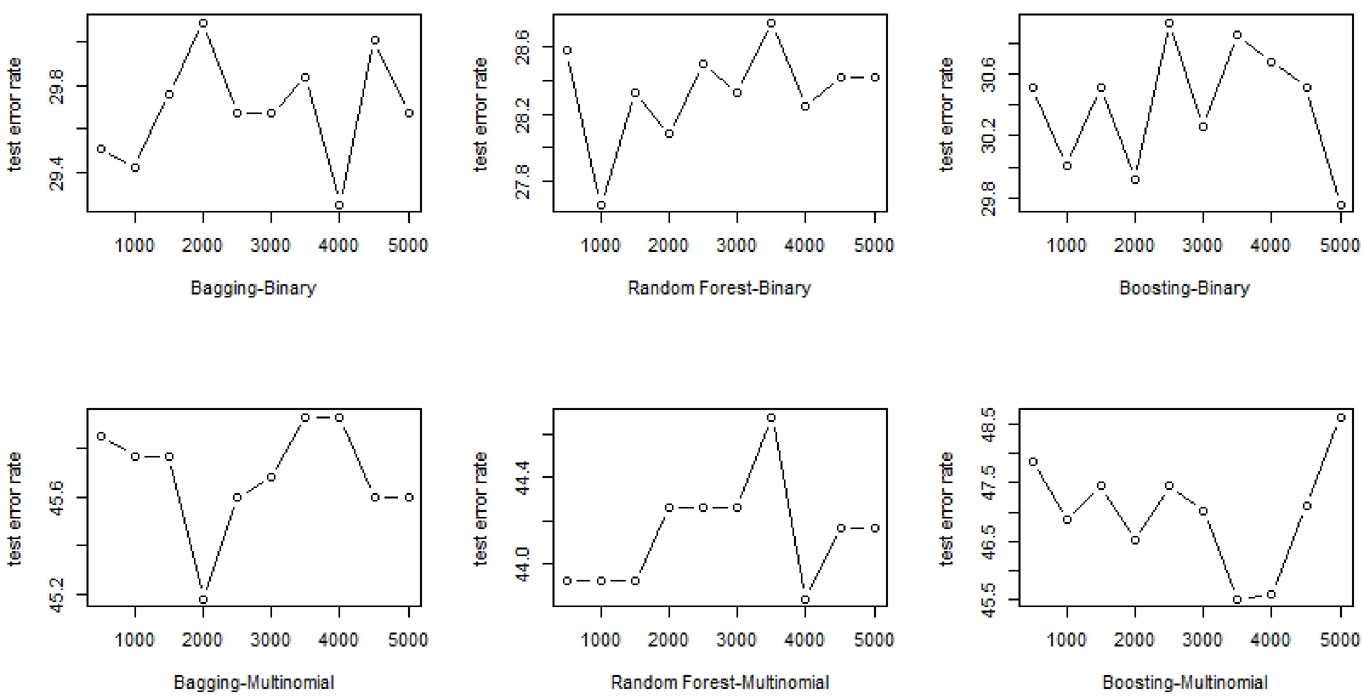

Figure 7: The Testing Error with Different Numbers of Bootstraps

5.2.3 Imbalance Issue

The improvement of the false negative rate in the multinomial setting is our priority in this project. If we can find the best model to correctly predict the five levels of suicide risk (NSR/LSR/MSR/HSR/ISR), we can rank the prediction probability and provide the name list to TNSPH to contact the callers immediately.

The high false negative rate is possibly associated with the imbalanced distribution of the suicide risk outcome. Among the five suicide risk groups in the dataset, the proportion of HSR and ISR are exceptionally small: 1.63% and 1.81%, respectively. However, most machine learning classification methods are unable to calculate imbalanced data correctly. The minority groups (HSR/ISR) are likely to be misclassified to the majority group, which is NSR or LSR. TNSPH will lose the opportunity to save lives if we underestimate the high-risk callers.

We proved the misclassification situation by experimenting with the following scenarios. To simplify the issue, we separated the five suicide risk groups into two groups. Since the suicide risk outcome is ordinal data, we can focus on only four types of sub-multinomial models. Figure 8 summarizes the result from the Random Forest model where the number of Bootstraps is assigned to 500.

The imbalance between the binary groups increases from model 1 to model 4. We observe the imbalance proportion as 51.96% in model 1 and 1.81% in model 4. This imbalance issue causes the false negative error of the suicide risk group to increase. To elaborate, when the data is balanced (model 1), the false negative rate calculated from the confusion matrix is only 23%. When the imbalance issue is gradually introduced in the dataset (from model 2 to model 4), the false negative rate increases to 100%. This indicates that the imbalanced data will bias the prediction of the TRUE high suicide risk group towards the majority case, the group with no suicide risk. In other words, the imbalance issue may produce a completely wrong prediction for suicide risk assessment.

Model	Data	Group "No"	Group "Yes"	Random Forest	Confusion Matrix								
				Testing Error		Truth							
1	Group	1	2345	27.07%			Y	N	TTL		Y	N	TTL
		NSR	LSR/MSR/HSR/ISR			Y	453	190	643	Y	77%	31%	54%
	#	2866	3100			N	133	417	550	N	23%	69%	46%
	%	48.04%	51.96%			TTL	586	607	1193	TTL	100%	100%	100%
2	Group	12	345	18.44%			Y	N	TTL		Y	N	TTL
		NSR/LSR	MSR/HSR/ISR			Y	48	57	105	Y	23%	6%	9%
	#	4827	1144			N	162	926	1088	N	77%	94%	91%
	%	80.91%	19.18%		Prediction	TTL	210	983	1193	TTL	100%	100%	100%
3	Group	123	45	2.35%			Y	N	TTL		Y	N	TTL
		NSR/LSR/MSR	HSR/ISR			Y	0	2	2	Y	0%	0%	0%
	#	5761	205			N	26	1165	1191	N	100%	100%	100%
	%	96.56%	3.44%			TTL	26	1167	1193	TTL	100%	100%	100%
4	Group	1234	5	1.59%			Y	N	TTL		Y	N	TTL
		NSR/LSR/MSR/HSR	ISR			Y	0	0	0	Y	0%	0%	0%
	#	5858	108			N	19	1174	1193	N	100%	100%	100%
	%	98.19%	1.81%			TTL	19	1174	1193	TTL	100%	100%	100%

Figure 8: The Minority Group being misclassified towards to the Majority Group due to Imbalanced Data

It is crucial to overcome the imbalance issues and find the best model with a lower false negative rate. Haibo He and Garcia (2009) suggest that balancing the data is a straightforward solution to improve model performance, and recommends performing undersampling or oversampling methods to reduce the testing error. Here we define the minority group as the group which causes the imbalance issue, and the majority group as the group which occupies a more substantial proportion in the dataset.

The undersampling method reduces the sample size from the majority group. We randomly select the sample from the majority group to match the sample size of the minority group. The advantage of this method is to maintain as much information as possible in the minority group. However, we may lose potential information from the excluded sample of the majority group.

Since the sample size of the minority groups, HSR/ISR are 97 and 108, respectively, we first perform Simple Random Sampling to select 100 cases in each minority group, and then randomly sample 100 cases from each majority group (NSR/LSR/MSR). When the five group are combined to a new dataset, the total sample size is 500. For evaluating the testing error and false negative rate, we separate the new dataset into training and testing datasets with sample sizes 400 and 100, respectively.

Here we only explore the best three classification models revealed in the previous analysis, which are Random Forest, Bagging, and Boosting. The result of Random Forest shown in Figure 9-13. Figures 24-29 in the appendix summarize the similar effects of the Bagging and Boosting techniques.

Since the result may be affected by the random seed, we simulate the Random Forest Model 100 times and summarize the results in Figure 9. The average testing error of the Undersampling Random Forest Model is worse (48.13%) than the original Random Forest Model without balancing the data (44.20%). The reason may be that key information is lost in the majority groups due to the smaller sample size (size = 100 v.s. 1093).

Although the average test error does not improve, the average false negative rate of high suicide risk groups (MSR/HSR/ISR) significantly decreases from 77.09%/99.11%/90.36% to 64.85%/32.15%/27.50%. This indicates that the undersampling method can solve the imbalanced issue and reduce the false negative rate of each suicide risk group.

[Undersampling - Simple Random Sampling] maintain same scale of sample size of minority group- Random Forest															
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	11.10	5.67	3.36	0.74	1.04	21.91	Predict	NSR	51%	26%	15%	3%	5%	100%
	LSR	4.28	5.67	4.11	1.32	1.02	16.40		LSR	26%	35%	25%	8%	6%	100%
	MSR	2.61	4.77	7.03	2.51	1.82	18.74		MSR	14%	25%	38%	13%	10%	100%
	HSR	0.97	2.12	3.05	13.57	1.62	21.33		HSR	5%	10%	14%	64%	8%	100%
	ISR	1.04	1.77	2.45	1.86	14.50	21.62		ISR	5%	8%	11%	9%	67%	100%
	TTL	20.00	20.00	20.00	20.00	20.00	100.00		TTL	20%	20%	20%	20%	20%	100%
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	11%	6%	3%	1%	1%	22%	Predict	NSR	56%	28%	17%	4%	5%	22%
	LSR	4%	6%	4%	1%	1%	16%		LSR	21%	28%	21%	7%	5%	16%
	MSR	3%	5%	7%	3%	2%	19%		MSR	13%	24%	35%	13%	9%	19%
	HSR	1%	2%	3%	14%	2%	21%		HSR	5%	11%	15%	68%	8%	21%
	ISR	1%	2%	2%	2%	15%	22%		ISR	5%	9%	12%	9%	73%	22%
	TTL	20%	20%	20%	20%	20%	100%		TTL	100%	100%	100%	100%	100%	100%
Testing Error		48.13%		Sen	50.96%	Spe	55.50%	FP/FN		44.50%	71.65%	64.85%	32.15%	27.50%	49.04%

Figure 9: Undersampling + SRS - Random Forest Multinomial Model

The oversampling method duplicates the samples from the minority group randomly. We used Simple Random Sampling method and extended the sample size of the minority group, and then matched the sample size to each group in the dataset. The advantage of this process is that not only can it balance the dataset but it also avoids losing information from the minority cases. However, the major disadvantage of this method is that it runs the risk of overfitting the model. That is, the training dataset is more likely to be dependent on the testing dataset when we produce a larger duplicated sample. This will lead to overestimating model performance and reduce the generalizability.

Next, we apply the oversampling method to our imbalanced data. We multiplied the sample size of the minority groups HSR/ISR by 5 times (size = $5X100 = 500$). To balance the data, we also randomly sample the same sample size from the majority groups. That is to say, we have 500 cases in each group, and the total size of the new dataset is 2500. We separate the dataset into a training dataset and a testing dataset to verify the model performance. Then, we analyze the effects on the testing error and the false negative rate of suicide risk groups based on the Oversampling Random Forest model.

We compare the model performance in the oversampling model to the original Random Forest Model (imbalanced data). The oversampling method can significantly improve both the testing error and the false negative rate. After 100 simulations (Figure 10), the average testing error is considerably reduced from 44.20% to 27.95%. Most importantly, the false negative rate of high suicide risk groups (MSR/HSR/ISR) significantly reduces from 77.09%/99.11%/90.36% to 41.83%/6.58%/2.93%. Thus, the oversampling method outperforms both the original Random Forest model and the undersampling model.

Next, we observe the larger sample effect on the oversampling method by multiplying the sample size by 10 times instead of five. Increasing the sample size through oversampling does improve the testing error and the false positive rate. After 100 simulations, the average testing error drops to 21.46% and the false negative error decreases to 29.19%/5.31%/1.18% (Figure 11). However, the significant improvement is caused by the overfitting issue. The oversampling method is not an ideal solution because the overfitting model would not likely fit the new data well.

[Oversampling - Simple Random Sampling] 5 times sample size of minority group- Random Forest															
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
	NSR	67.12	24.47	10.36	0.19	0.32	102.46		NSR	66%	24%	10%	0%	0%	100%
	LSR	18.20	44.49	18.05	0.48	0.34	81.56		LSR	22%	55%	22%	1%	0%	100%
Predict	MSR	10.30	21.75	58.17	0.74	0.86	91.82	Predict	MSR	11%	24%	63%	1%	1%	100%
	HSR	1.77	4.59	6.23	93.42	1.41	107.42		HSR	2%	4%	6%	87%	1%	100%
	ISR	2.61	4.70	7.19	5.17	97.07	116.74		ISR	2%	4%	6%	4%	83%	100%
	TTL	100.00	100.00	100.00	100.00	100.00	500.00		TTL	20%	20%	20%	20%	20%	100%
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
	NSR	13%	5%	2%	0%	0%	20%		NSR	67%	24%	10%	0%	0%	20%
	LSR	4%	9%	4%	0%	0%	16%		LSR	18%	44%	18%	0%	0%	16%
Predict	MSR	2%	4%	12%	0%	0%	18%	Predict	MSR	10%	22%	58%	1%	1%	18%
	HSR	0%	1%	1%	19%	0%	21%		HSR	2%	5%	6%	93%	1%	21%
	ISR	1%	1%	1%	1%	19%	23%		ISR	3%	5%	7%	5%	97%	23%
	TTL	20%	20%	20%	20%	20%	100%		TTL	100%	100%	100%	100%	100%	100%
Testing Error		27.95%		Sen	73.29%	Spe	67.12%	FP/FN		32.88%	55.51%	41.83%	6.58%	2.93%	26.71%

Figure 10: Oversampling + SRS 5 times sample size - Random Forest Multinomial Model

[Oversampling - Simple Random Sampling] 10 times sample size of minority group- Random Forest															
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
	NSR	145.25	41.23	14.05	0.03	0.02	200.58		NSR	72%	21%	7%	0%	0%	100%
	LSR	31.65	111.49	25.10	0.03	0.10	168.37		LSR	19%	66%	15%	0%	0%	100%
Predict	MSR	16.60	35.15	141.63	0.13	0.54	194.05	Predict	MSR	9%	18%	73%	0%	0%	100%
	HSR	2.61	5.16	7.30	189.38	1.70	206.15		HSR	1%	3%	4%	92%	1%	100%
	ISR	3.89	6.97	11.92	10.43	197.64	230.85		ISR	2%	3%	5%	5%	86%	100%
	TTL	200.00	200.00	200.00	200.00	200.00	1000.00		TTL	20%	20%	20%	20%	20%	100%
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
	NSR	15%	4%	1%	0%	0%	20%		NSR	73%	21%	7%	0%	0%	20%
	LSR	3%	11%	3%	0%	0%	17%		LSR	16%	56%	13%	0%	0%	17%
Predict	MSR	2%	4%	14%	0%	0%	19%	Predict	MSR	8%	18%	71%	0%	0%	19%
	HSR	0%	1%	1%	19%	0%	21%		HSR	1%	3%	4%	95%	1%	21%
	ISR	0%	1%	1%	1%	20%	23%		ISR	2%	3%	6%	5%	99%	23%
	TTL	20%	20%	20%	20%	20%	100%		TTL	100%	100%	100%	100%	100%	100%
Testing Error		21.46%		Sen	80.02%	Spe	72.63%	FP/FN		27.38%	44.26%	29.19%	5.31%	1.18%	19.98%

Figure 11: Oversampling + SRS 10 times sample size- Random Forest Multinomial Model

The overfitting issue is caused by the Simple Random Sampling method. The larger sample size we obtain, the more serious the overfitting because there is a greater chance of increased dependent information. There are several solutions to deal with the overfitting issue. One possible way is generate an artificial dataset to extract a sample, rather than using the original dataset. Synthetic Minority Oversampling Technique (SMOTE) is a well-known and common tool to deal with the overfitting issue (Chawla et al., 2002).

The SMOTE algorithm creates an artificial dataset. The new dataset could be generated by calculating the Euclidean distance among the K-nearest neighbors of original dataset. For instance, for each data point in the minority group, we find the nearest 10 data points around that original data point and use a weight to create a new data point whose characteristics are similar to the original data point. Since the existing R package is not easy to apply to the existing dataset, the SMOTE algorithm was applied to produce the function. The Gower distance is used in this SMOTE function, instead of Euclidean distance, because Gower distance can help measure the categorical variables in the dataset.

Figure 12 is the result after performing the SMOTE procedure. The performance of the SMOTE model is as good as the Simple Random Sampling model. After 100 simulations, the average testing error and the false negative rate of high suicide risk groups (MSR/HSR/ISR) both significantly improve compared to the original setting. The model performance could be continually enhanced by increasing the sample size through SMOTE procedure (Figure 13), reducing the overfitting issue. Therefore, the SMOTE model was selected as the best model because SMOTE does help solve the imbalanced problem in the dataset by providing a better sampling strategy.

[Oversampling - SMOTE] 5 times sample size of minority group- Random Forest															
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	67.11	24.22	9.92	0.27	0.19	101.71	Predict	NSR	65%	24%	10%	0%	0%	99%
	LSR	17.74	42.82	18.99	0.29	0.39	80.23		LSR	22%	53%	23%	0%	0%	98%
	MSR	10.31	23.10	56.13	0.81	1.39	91.74		MSR	11%	25%	61%	1%	2%	100%
	HSR	2.14	4.93	6.96	94.00	1.72	109.75		HSR	2%	5%	6%	88%	2%	102%
	ISR	2.70	4.93	8.00	4.63	96.31	116.57		ISR	2%	4%	7%	4%	82%	100%
	TTL	100.00	100.00	100.00	100.00	100.00	500.00		TTL	20%	20%	20%	20%	20%	100%
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	13%	5%	2%	0%	0%	20%	Predict	NSR	67%	24%	10%	0%	0%	20%
	LSR	4%	9%	4%	0%	0%	16%		LSR	18%	43%	19%	0%	0%	16%
	MSR	2%	5%	11%	0%	0%	18%		MSR	10%	23%	56%	1%	1%	18%
	HSR	0%	1%	1%	19%	0%	22%		HSR	2%	5%	7%	94%	2%	22%
	ISR	1%	1%	2%	1%	19%	23%		ISR	3%	5%	8%	5%	96%	23%
	TTL	20%	20%	20%	20%	20%	100%		TTL	100%	100%	100%	100%	100%	100%
Testing Error		28.73%		Sen	72.32%	Spe	67.11%	FP/FN		32.89%	57.18%	43.87%	6.00%	3.69%	27.69%

Figure 12: Oversampling + SMOTE 5 times sample size - Random Forest Multinomial Model

[Oversampling - SMOTE] 10 times sample size of minority group- Random Forest															
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	143.70	42.06	15.18	0.00	0.01	200.95	Predict	NSR	72%	21%	8%	0%	0%	100%
	LSR	32.63	105.26	30.02	0.00	0.00	167.91		LSR	19%	63%	18%	0%	0%	100%
	MSR	16.80	39.02	133.53	0.13	0.69	190.17		MSR	9%	20%	69%	0%	0%	98%
	HSR	2.70	6.62	8.74	190.80	2.44	211.30		HSR	1%	3%	4%	93%	1%	102%
	ISR	4.17	7.04	12.53	9.07	196.86	229.67		ISR	2%	3%	5%	4%	85%	99%
	TTL	200.00	200.00	200.00	200.00	200.00	1000.00		TTL	20%	20%	20%	20%	20%	100%
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	14%	4%	2%	0%	0%	20%	Predict	NSR	72%	21%	8%	0%	0%	20%
	LSR	3%	11%	3%	0%	0%	17%		LSR	16%	53%	15%	0%	0%	17%
	MSR	2%	4%	13%	0%	0%	19%		MSR	8%	20%	67%	0%	0%	19%
	HSR	0%	1%	1%	19%	0%	21%		HSR	1%	3%	4%	95%	1%	21%
	ISR	0%	1%	1%	1%	20%	23%		ISR	2%	4%	6%	5%	98%	23%
	TTL	20%	20%	20%	20%	20%	100%		TTL	100%	100%	100%	100%	100%	100%
Testing Error		22.99%		Sen	78.31%	Spe	71.85%	FP/FN		28.15%	47.37%	33.24%	4.60%	1.57%	21.69%

Figure 13: Oversampling + SMOTE 10 times sample size - Random Forest Multinomial Model

5.3 Predict CANTE group

The Oversampling SMOTE Random Forest Model is the best model. This model is used to predict the suicide risk for the CANTE group (Figure 14). The total sample size of the CANTE group is 9803. After this prediction, it was found that 254 and 177 belong to the ISR and HSR group, respectively.

These process was used to evaluate which caller have the highest probability of belonging to the ISR group. If the prediction probability of the ISR group is prioritized, 61 people are identified with risk probabilities exceeding 0.80. These people are at the highest risk of suicide because they have the highest opportunity of belonging to the ISR group. In other words, TNSPH may prioritize contacting these 61 people.

NSR	LSR	MSR	HSR	ISR	Total
6127	2289	956	177	254	9803
63%	23%	10%	2%	3%	100%

Risk Index	Frequency	Cumulative Frequency	Percent	Cumulative Percent
0.95 - 1.00	27	27	0.28%	0.28%
0.90 - 0.95	15	42	0.15%	0.43%
0.85 - 0.90	12	54	0.12%	0.55%
0.80 - 0.85	7	61	0.07%	0.62%
0.75 - 0.80	17	78	0.17%	0.80%
0.70 - 0.75	7	85	0.07%	0.87%
0.65 - 0.70	16	101	0.16%	1.03%
0.60 - 0.65	14	115	0.14%	1.17%
0.55 - 0.60	16	131	0.16%	1.34%
0.50 - 0.55	14	145	0.14%	1.48%
below 0.60	9658	9803	98.52%	100.00%

* Predict ISR : 254 People

Figure 14: Prediction Result

6 Conclusion and Discussion

In this project, we initially applied eight machine learning classification methods to the binary and multinomial models to predict high-risk suicide groups in TNSPH data. Random Forest, Boosting, and Bagging are the best three methods to lower the average testing error. However, the average testing error in the multinomial model still reaches 44.20%/45.93%/45.94%, respectively. Although the testing error in binary model performs better (28.03%/30.03%/29.07%), the multinomial model is preferred because it allows for the prediction of different levels of suicide risk. This will effectively and efficiently identify individuals in need of immediate attention.

As a result, reducing the false negative rate of suicide risk groups (MSR/HSR/ISR) in the multinomial model is the priority. Since the TNSPH data is exceptionally imbalanced, efforts were concentrated on identifying sampling methods that balance the data and improve the model. Figure 15 summarizes the results of the Random Forest Multinomial models. Each model was simulated 100 times to confirm the model performance. The Oversampling SMOTE Random Forest Model is the best model because it 1) overcame the imbalanced issue 2) reduced the average testing error, 3) considerably improved the average false negative rate of high suicide risk groups (MSR/HSR/ISR), and 4) avoided the overfitting issue caused by Simple Random Sampling.

100 Simulations		Scale of minority group	Testing Error			False Negative Rate						
			Bagging	Boosting	Random Forest	Bagging	Boosting	Random Forest	Random Forest			
									LSR	MSR	HSR	ISR
Original Setting		-	45.93%	45.94%	44.20%	65.55%	65.73%	65.25%	56.50%	77.09%	99.11%	90.36%
Undersampling	Simple Random Sampling	1 times	49.52%	51.34%	48.13%	49.46%	50.34%	49.04%	71.65%	64.85%	32.15%	27.50%
	SMOTE		51.19%	53.45%	50.13%	52.26%	53.46%	52.06%	71.25%	65.50%	38.20%	33.30%
Oversampling	Simple Random Sampling	5 times	28.10%	31.33%	27.95%	25.84%	28.88%	26.71%	55.51%	41.83%	6.58%	2.93%
	SMOTE		28.74%	31.89%	28.73%	26.66%	29.59%	27.69%	57.18%	43.87%	6.00%	3.69%
	Simple Random Sampling	10 times	20.70%	27.10%	21.46%	18.34%	24.49%	19.98%	44.26%	29.19%	5.31%	1.18%
	SMOTE		22.42%	28.24%	22.99%	20.24%	25.92%	21.69%	47.37%	33.24%	4.60%	1.57%

Figure 15: The Performance for the Random Forest Multinomial Models

Finally, we may use the Oversampling SMOTE Random Forest Model to predict which individuals may be at high-risk for suicide when an accurate assessment cannot be made during the phone call (CANTE group). 61 people in the CANTE group were identified who have higher suicide risk and the prioritized list was provided to TNSPH.

Future work may explore which different machine learning classification methods and sampling strategies improve model performance. The relationship between these essential factors and suicide risk also warrants further exploration. Bagging and Random Forest methods in the SMOTE model both suggest that the most important predictors are the primary concern, previous suicide attempt, call day, call month, and call time (Figure 30 in the appendix). The results match with the subjective findings from the exploratory data analysis. A longitudinal model combined with machine learning methods may be necessary to further analyze call behavior to help predict suicide risk.

Most of the research on suicide prevention hotlines focuses on caller characteristics and prevention performance from the psychologist perspective. There is little literature about applying machine learning techniques to identify individuals at high-risk of suicide. This research demonstrates that there is opportunity to utilize machine learning approaches to effectively identify and reach individuals in need of assistance, saving countless lives in the future.

7 Acknowledgements

I appreciate the methodology suggestions from Dr. Sreenivas Konda. Thanks for proofreading support from the SPH Writing Specialist, Anna Yankelev.

References

Chawla, N. V., Bowyer, K. W., Hall, L. O., and Kegelmeyer, W. P. (2002). SMOTE: Synthetic minority over-sampling technique. *Journal of Artificial Intelligence Research*, 16:321–357.

Christopher Lukas, H. M. S. (2007). *Silent Grief*. Jessica Kingsley Publishers.

Haibo He, Member, I. and Garcia, E. A. (2009). Learning from imbalanced data. *IEEE Transactions on Knowledge and Data Engineering*, 21(9):1263–1284.

Shaw, F. F.-T. and Chiang, W.-H. (2019). An evaluation of suicide prevention hotline results in taiwan: Caller profiles and the effect on emotional distress and suicide risk. *Journal of Affective Disorders*, 244:16–20.

Valtonen, H., Suominen, K., Partonen, T., Ostamo, A., and Lönnqvist, J. (2006). Time patterns of attempted suicide. *Journal of Affective Disorders*, 90(2-3):201–207.

Wenz, F. V. (1977). Seasonal suicide attempts and forms of loneliness. *Psychological Reports*, 40(3):807–810.

Woodward, A. and Wyllie, C. (2016). Helplines, tele-web support services, and suicide prevention. In *The International Handbook of Suicide Prevention*, pages 490–504. John Wiley & Sons, Ltd.

8 Appendix

		Suicide Risk Assement Result						Suicide Risk Assement Result					
		NSR	LSR	MSR	HSR	ISR	Total	NSR	LSR	MSR	HSR	ISR	Total
	Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	2866	1956	939	97	108	5966
Gender	**1.Male**	**31.5%**	**39.5%**	**42.7%**	**63.9%**	**60.2%**	**36.9%**	903	773	401	62	65	2204
	2.Female	68.5%	60.5%	57.3%	36.1%	39.8%	63.1%	1963	1183	538	35	43	3762
Age	1. < 19 y	4.4%	3.3%	2.1%	3.1%	1.9%	3.6%	125	65	20	3	2	215
	2. 20-29 y	17.8%	18.1%	15.4%	12.4%	14.8%	17.4%	510	354	145	12	16	1037
	3. 30-39 y	32.0%	29.1%	28.2%	27.8%	23.1%	30.2%	917	569	265	27	25	1803
	4. 40-49 y	29.8%	28.5%	30.2%	26.8%	21.3%	29.2%	855	557	284	26	23	1745
	5. 50-59 y	**14.0%**	**16.0%**	**19.5%**	**24.7%**	**37.0%**	**16.1%**	400	313	183	24	40	960
	6. >60 y	2.1%	5.0%	4.5%	5.2%	1.9%	3.5%	59	98	42	5	2	206
Marriage Status	1.Single	51.3%	45.1%	41.6%	37.1%	30.6%	47.2%	1471	883	391	36	33	2814
	2.Married/Cohabitation	21.8%	21.3%	22.6%	20.6%	13.0%	21.6%	624	416	212	20	14	1286
	3.Separated	2.7%	2.4%	3.2%	5.2%	4.6%	2.7%	76	47	30	5	5	163
	4.Divorced	**21.5%**	**25.5%**	**26.2%**	**32.0%**	**23.1%**	**23.8%**	617	499	246	31	25	1418
	5.Widowed	**2.7%**	**5.7%**	**6.4%**	**5.2%**	**28.7%**	**4.8%**	78	111	60	5	31	285
Residential Type	1.City	49.2%	53.1%	54.1%	44.3%	36.1%	50.9%	1409	1039	508	43	39	3038
	2.Countryside	**50.8%**	**46.9%**	**45.9%**	**55.7%**	**63.9%**	**49.1%**	1457	917	431	54	69	2928
Living company	1.No Company	24.0%	26.3%	28.2%	38.1%	20.4%	25.6%	688	515	265	37	22	1527
	2.Live with Family	71.1%	68.9%	68.8%	57.7%	77.8%	69.9%	2039	1348	646	56	84	4173
	3.Live with Friends/Others	4.8%	4.8%	3.0%	4.1%	1.9%	4.5%	139	93	28	4	2	266
Education	**1.Primary School**	**2.3%**	**5.1%**	**5.2%**	**18.6%**	**5.6%**	**4.0%**	67	99	49	18	6	239
	2.Junior High School	**14.2%**	**18.6%**	**22.9%**	**22.7%**	**16.7%**	**17.2%**	406	363	215	22	18	1024
	3.Senior High School	**38.8%**	**38.5%**	**40.9%**	**42.3%**	**62.0%**	**39.5%**	1111	753	384	41	67	2356
	4.Vocational School;	15.3%	12.4%	8.1%	9.3%	5.6%	12.9%	439	242	76	9	6	772
	5.College and University	25.8%	23.0%	19.1%	7.2%	10.2%	23.2%	738	450	179	7	11	1385
	6.Graduate School	3.7%	2.5%	3.8%	0.0%	0.0%	3.2%	105	49	36	0	0	190
	Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	2866	1956	939	97	108	5966
Job	1.Service Industry	20.8%	18.5%	14.6%	9.3%	7.4%	18.6%	595	362	137	9	8	1111
	2.Commerical Industry	6.9%	2.7%	1.6%	1.0%	1.9%	4.5%	198	53	15	1	2	269
	3.Manufacturing Industry	4.2%	5.6%	6.8%	7.2%	9.3%	5.2%	119	109	64	7	10	309
	4.Military/Police/Public Servant	1.7%	2.1%	1.7%	0.0%	0.0%	1.8%	49	41	16	0	0	106
	5.Self-Employment	4.9%	3.3%	3.4%	0.0%	0.0%	4.0%	141	65	32	0	0	238
	6.Student	5.1%	4.6%	2.9%	5.2%	2.8%	4.5%	146	90	27	5	3	271
	7.Housewife	10.0%	8.2%	8.4%	6.2%	4.6%	9.0%	288	160	79	6	5	538
	8.Retired	2.9%	3.7%	4.9%	5.2%	4.6%	3.6%	84	72	46	5	5	212
	9.Unemployed	**43.5%**	**51.3%**	**55.7%**	**66.0%**	**69.4%**	**48.8%**	1246	1004	523	64	75	2912
	Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	2866	1956	939	97	108	5966
Income	1.Job	25.8%	26.6%	23.0%	21.6%	21.3%	25.5%	739	521	216	21	23	1520
	2.Savingï¼Pension	10.2%	11.2%	13.7%	11.3%	10.2%	11.1%	292	220	129	11	11	663
	3.Subsidy	20.8%	23.6%	25.1%	24.7%	37.0%	22.8%	597	462	236	24	40	1359
	4.Family Support	43.2%	38.5%	38.1%	42.3%	31.5%	40.6%	1238	753	358	41	34	2424
	Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	2866	1956	939	97	108	5966

Figure 16: Contingency Table 01

		Suicide Risk Assement Result						Suicide Risk Assement Result					
		NSR	LSR	MSR	HSR	ISR	Total	NSR	LSR	MSR	HSR	ISR	Total
	Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	2866	1956	939	97	108	5966
Mental Health Status	1.Normal	10.3%	4.4%	3.1%	1.0%	.9%	6.9%	294	87	29	1	1	412
	2.Mental Illness	**79.7%**	**84.8%**	**87.5%**	**86.6%**	**92.6%**	**82.9%**	2283	1658	822	84	100	4947
	3.Suspect Mental Illness	10.1%	10.8%	9.4%	12.4%	6.5%	10.2%	289	211	88	12	7	607
	Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	2866	1956	939	97	108	5966
Substance Abuse	1.No	81.8%	69.2%	57.4%	41.2%	33.3%	72.3%	2345	1353	539	40	36	4313
	2.Alcohol Addiction	**10.9%**	**17.4%**	**23.1%**	**29.9%**	**25.9%**	**15.5%**	311	341	217	29	28	926
	3.Medicine Addiction	**5.2%**	**10.1%**	**14.4%**	**17.5%**	**38.0%**	**9.1%**	150	197	135	17	41	540
	4.Drug Addiction	**2.1%**	**3.3%**	**5.1%**	**11.3%**	**2.8%**	**3.1%**	60	65	48	11	3	187
	Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	2866	1956	939	97	108	5966
Exposure to Violence	1.No Exposure to Violence	78.7%	69.3%	65.6%	54.6%	50.9%	72.6%	2255	1355	616	53	55	4334
	2.Abuser	**6.7%**	**10.6%**	**13.3%**	**26.8%**	**34.3%**	**9.8%**	192	207	125	26	37	587
	3.Victim	13.5%	17.3%	18.4%	15.5%	14.8%	15.6%	386	338	173	15	16	928
	4.Hurting Each Other	1.2%	2.9%	2.7%	3.1%	0.0%	2.0%	33	56	25	3	0	117
	Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	2866	1956	939	97	108	5966
Primary Concern	1.Emotional Issue	8.4%	7.0%	4.7%	4.1%	4.6%	7.2%	240	137	44	4	5	430
	2.Marriage Issue	3.6%	3.5%	3.0%	3.1%	1.9%	3.4%	102	68	28	3	2	203
	3.Family Issue	14.5%	15.1%	18.0%	11.3%	24.1%	15.4%	416	296	169	11	26	918
	4.Interpersonal Issue	9.4%	5.1%	4.9%	7.2%	2.8%	7.1%	268	99	46	7	3	423
	5.Mental Health Issues	**24.6%**	**30.4%**	**31.4%**	**40.2%**	**33.3%**	**28.0%**	705	594	295	39	36	1669
	6.Substance Abuse (Alcohol, Drug)	11.6%	11.9%	14.0%	8.2%	7.4%	11.9%	332	232	131	8	8	711
	7.Substance Abuse (NON Alcohol, Drug)	1.1%	1.9%	2.8%	2.1%	3.7%	1.7%	31	37	26	2	4	100
	9.Physical Health Issue	5.9%	6.2%	7.1%	5.2%	1.9%	6.1%	169	121	67	5	2	364
	10.Unemployment Issue	**3.1%**	**5.8%**	**4.7%**	**11.3%**	**10.2%**	**4.5%**	88	113	44	11	11	267
	13.Career Issue	7.4%	3.8%	1.7%	3.1%	1.9%	5.1%	211	74	16	3	2	306
	18.Life-Adjustment Issue	8.9%	6.9%	4.8%	2.1%	6.5%	7.4%	255	135	45	2	7	444
	19.Major Loss	.6%	.6%	1.2%	1.0%	0.0%	.7%	16	12	11	1	0	40
	20.Crime or Illeage Issue	1.2%	1.9%	1.8%	1.0%	1.9%	1.5%	33	38	17	1	2	91
Access Care for Primary Concern	1.Not Seeking for Medical Support	16.1%	11.7%	8.7%	14.4%	9.3%	13.3%	461	228	82	14	10	795
	2.Already Seek for Medical Support	71.3%	73.1%	72.2%	66.0%	86.1%	72.2%	2043	1430	678	64	93	4308
	3.Not Regularly have Medical Support	11.3%	13.3%	15.4%	16.5%	3.7%	12.6%	324	260	145	16	4	749
	4.Refuse Medical Support	1.3%	1.9%	3.6%	3.1%	.9%	1.9%	38	38	34	3	1	114
Previous Suicide Attempt	1.No	49.1%	26.9%	16.3%	12.4%	6.5%	35.3%	1406	526	153	12	7	2104
	2.Yes	**50.9%**	**73.1%**	**83.7%**	**87.6%**	**93.5%**	**64.7%**	1460	1430	786	85	101	3862

Figure 17: Contingency Table 02

		Suicide Risk Assement Result						Suicide Risk Assement Result					
		NSR	LSR	MSR	HSR	ISR	Total	NSR	LSR	MSR	HSR	ISR	Total
	Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	2866	1956	939	97	108	5966
Call Frequency	1.Repeated Caller	95.5%	96.3%	97.6%	97.9%	97.2%	96.2%	2737	1884	916	95	105	5737
	2.First-Time Caller	4.5%	3.7%	2.4%	2.1%	2.8%	3.8%	129	72	23	2	3	229
Call Duration	1.Call duration less than 20mins	76.5%	64.8%	52.4%	49.5%	65.7%	68.2%	2193	1267	492	48	71	4071
	2.Call duration 20-40mins	18.1%	26.9%	31.8%	28.9%	20.4%	23.4%	518	527	299	28	22	1394
	3.Call duration more than 40mins	**5.4%**	**8.3%**	**15.8%**	**21.6%**	**13.9%**	**8.4%**	155	162	148	21	15	501
Call Month	1.Spring	28.8%	25.9%	31.3%	24.7%	37.0%	28.3%	825	506	294	24	40	1689
	2.Summer	25.2%	29.3%	22.6%	26.8%	25.0%	26.1%	721	574	212	26	27	1560
	3.Fall	20.1%	24.0%	23.7%	19.6%	23.1%	22.0%	575	469	223	19	25	1311
	4.Winter	**26.0%**	**20.8%**	**22.4%**	**28.9%**	**14.8%**	**23.6%**	745	407	210	28	16	1406
Call Day	Monday	13.5%	12.6%	14.6%	11.3%	14.8%	13.4%	388	246	137	11	16	798
	Tuesday	14.0%	14.1%	16.1%	18.6%	14.8%	14.4%	400	276	151	18	16	861
	Wednesday	14.3%	15.5%	13.0%	19.6%	11.1%	14.5%	409	303	122	19	12	865
	Thursday	15.9%	14.6%	17.1%	8.2%	16.7%	15.6%	457	285	161	8	18	929
	Friday	14.6%	15.7%	14.0%	15.5%	16.7%	14.9%	418	308	131	15	18	890
	Saturday	13.7%	14.6%	12.5%	14.4%	13.9%	13.8%	392	285	117	14	15	823
	Sunday	14.0%	12.9%	12.8%	12.4%	12.0%	13.4%	402	253	120	12	13	800
Call Time	1.Day Shift	31.9%	27.2%	22.9%	22.7%	26.9%	28.7%	914	533	215	22	29	1713
	2.Night Shift	**34.2%**	**46.3%**	**45.3%**	**46.4%**	**44.4%**	**40.3%**	981	905	425	45	48	2404
	3.Graveyard Shift	33.9%	26.5%	31.8%	30.9%	28.7%	31.0%	971	518	299	30	31	1849

Figure 18: Contingency Table 03

1.Naïve Bayes									
		TRUE					TRUE		
		Yes	No	TTL			Yes	No	TTL
Predict	Yes	413	192	605	Predict	Yes	68%	32%	100%
	No	207	381	588		No	35%	65%	100%
	TTL	620	573	1193		TTL	52%	48%	100%
		TRUE					TRUE		
		Yes	No	TTL			Yes	No	TTL
Predict	Yes	35%	16%	51%	Predict	Yes	67%	34%	51%
	No	17%	32%	49%		No	33%	66%	49%
	TTL	52%	48%	100%		TTL	100%	100%	100%
Test Error Rate	33.45%				False Positive	33.39%			

2.Naïve Bayes + Bagging									
		TRUE					TRUE		
		Yes	No	TTL			Yes	No	TTL
Predict	Yes	413	193	606	Predict	Yes	68%	32%	100%
	No	207	380	587		No	35%	65%	100%
	TTL	620	573	1193		TTL	52%	48%	100%
		TRUE					TRUE		
		Yes	No	TTL			Yes	No	TTL
Predict	Yes	35%	16%	51%	Predict	Yes	67%	34%	51%
	No	17%	32%	49%		No	33%	66%	49%
	TTL	52%	48%	100%		TTL	100%	100%	100%
Test Error Rate	33.53%				False Positive	33.39%			

3.Logistic Regression									
		TRUE					TRUE		
		Yes	No	TTL			Yes	No	TTL
Predict	Yes	440	202	642	Predict	Yes	69%	31%	100%
	No	180	371	551		No	33%	67%	100%
	TTL	620	573	1193		TTL	52%	48%	100%
		TRUE					TRUE		
		Yes	No	TTL			Yes	No	TTL
Predict	Yes	37%	17%	54%	Predict	Yes	71%	35%	54%
	No	15%	31%	46%		No	29%	65%	46%
	TTL	52%	48%	100%		TTL	100%	100%	100%
Test Error Rate	32.02%				False Positive	29.03%			

4.Logistic Regression + Bagging									
		TRUE					TRUE		
		Yes	No	TTL			Yes	No	TTL
Predict	Yes	411	187	598	Predict	Yes	69%	31%	100%
	No	209	386	595		No	35%	65%	100%
	TTL	620	573	1193		TTL	52%	48%	100%
		TRUE					TRUE		
		Yes	No	TTL			Yes	No	TTL
Predict	Yes	34%	16%	50%	Predict	Yes	66%	33%	50%
	No	18%	32%	50%		No	34%	67%	50%
	TTL	52%	48%	100%		TTL	100%	100%	100%
Test Error Rate	33.19%				False Positive	33.71%			

5.Decision Tree									
		TRUE					TRUE		
		Yes	No	TTL			Yes	No	TTL
Predict	Yes	329	156	485	Predict	Yes	68%	32%	100%
	No	291	417	708		No	41%	59%	100%
	TTL	620	573	1193		TTL	52%	48%	100%
		TRUE					TRUE		
		Yes	No	TTL			Yes	No	TTL
Predict	Yes	28%	13%	41%	Predict	Yes	53%	27%	41%
	No	24%	35%	59%		No	47%	73%	59%
	TTL	52%	48%	100%		TTL	100%	100%	100%
Test Error Rate	37.47%				False Positive	46.94%			

6.Bagging									
		TRUE					TRUE		
		Yes	No	TTL			Yes	No	TTL
Predict	Yes	435	168	603	Predict	Yes	72%	28%	100%
	No	185	405	590		No	31%	69%	100%
	TTL	620	573	1193		TTL	52%	48%	100%
		TRUE					TRUE		
		Yes	No	TTL			Yes	No	TTL
Predict	Yes	36%	14%	51%	Predict	Yes	70%	29%	51%
	No	16%	34%	49%		No	30%	71%	49%
	TTL	52%	48%	100%		TTL	100%	100%	100%
Test Error Rate	29.59%				False Positive	29.84%			

7.Random Forest									
		TRUE					TRUE		
		Yes	No	TTL			Yes	No	TTL
Predict	Yes	448	163	611	Predict	Yes	73%	27%	100%
	No	172	410	582		No	30%	70%	100%
	TTL	620	573	1193		TTL	52%	48%	100%
		TRUE					TRUE		
		Yes	No	TTL			Yes	No	TTL
Predict	Yes	38%	14%	51%	Predict	Yes	72%	28%	51%
	No	14%	34%	49%		No	28%	72%	49%
	TTL	52%	48%	100%		TTL	100%	100%	100%
Test Error Rate	28.08%				False Positive	27.74%			

8.Boosting									
		TRUE					TRUE		
		Yes	No	TTL			Yes	No	TTL
Predict	Yes	430	231	661	Predict	Yes	73%	27%	100%
	No	143	389	532		No	30%	70%	100%
	TTL	573	620	1193		TTL	52%	48%	100%
		TRUE					TRUE		
		Yes	No	TTL			Yes	No	TTL
Predict	Yes	36%	19%	55%	Predict	Yes	72%	28%	51%
	No	12%	33%	45%		No	28%	72%	49%
	TTL	48%	52%	100%		TTL	100%	100%	100%
Test Error Rate	31.35%				False Positive	27.74%			

Figure 19: Confusion Matrix- Binary Outcome

1.Naïve Bayes

		TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	429.08	195.47	62.17	3.84	4.99	695.55
	LSR	101.79	128.33	72.61	7.01	6.83	316.57
	MSR	33.17	49.04	42.19	5.02	3.40	132.82
	HSR	4.71	8.28	4.44	2.18	0.73	20.34
	ISR	4.25	9.88	6.59	0.95	6.05	27.72
	TTL	573.00	391.00	188.00	19.00	22.00	1193.00

		TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	62%	28%	9%	1%	1%	100%
	LSR	32%	41%	23%	2%	2%	100%
	MSR	25%	37%	32%	4%	3%	100%
	HSR	23%	41%	22%	11%	4%	100%
	ISR	15%	36%	24%	3%	22%	100%
	TTL	48%	33%	16%	2%	2%	100%

		TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	36%	16%	5%	0%	0%	58%
	LSR	9%	11%	6%	1%	1%	27%
	MSR	3%	4%	4%	0%	0%	11%
	HSR	0%	1%	0%	0%	0%	2%
	ISR	0%	1%	1%	0%	1%	2%
	TTL	48%	33%	16%	2%	2%	100%

		TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	75%	50%	33%	20%	23%	58%
	LSR	18%	33%	39%	37%	31%	27%
	MSR	6%	13%	22%	26%	15%	11%
	HSR	1%	2%	2%	11%	3%	2%
	ISR	1%	3%	4%	5%	28%	2%
	TTL	100%	100%	100%	100%	100%	100%

Testing Error	49.05%	Sen	28.83%	Spe	74.88%

FP/FN	25.12%	67.18%	77.56%	88.53%	72.50%	71.17%

2.Naïve Bayes + Bagging

		TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	429.69	196.05	62.38	3.83	5.00	696.95
	LSR	102.24	129.58	73.42	7.24	6.83	319.31
	MSR	33.53	49.02	42.17	4.98	3.52	133.22
	HSR	3.55	6.96	3.81	2.02	0.60	16.94
	ISR	3.99	9.39	6.22	0.93	6.05	26.58
	TTL	573.00	391.00	188.00	19.00	22.00	1193.00

		TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	62%	28%	9%	1%	1%	100%
	LSR	32%	41%	23%	2%	2%	100%
	MSR	25%	37%	32%	4%	3%	100%
	HSR	21%	41%	22%	12%	4%	100%
	ISR	15%	35%	23%	3%	23%	100%
	TTL	48%	33%	16%	2%	2%	100%

		TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	36%	16%	5%	0%	0%	58%
	LSR	9%	11%	6%	1%	1%	27%
	MSR	3%	4%	4%	0%	0%	11%
	HSR	0%	1%	0%	0%	0%	1%
	ISR	0%	1%	1%	0%	1%	2%
	TTL	48%	33%	16%	2%	2%	100%

		TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	75%	50%	33%	20%	23%	58%
	LSR	18%	33%	39%	38%	31%	27%
	MSR	6%	13%	22%	26%	16%	11%
	HSR	1%	2%	2%	11%	3%	1%
	ISR	1%	2%	3%	5%	28%	2%
	TTL	100%	100%	100%	100%	100%	100%

Testing Error	48.91%	Sen	29.00%	Spe	74.99%

FP/FN	25.01%	66.86%	77.57%	89.37%	72.50%	71.00%

Figure 20: Confusion Matrix- Multinomial Outcome 01

3.Multinomial Regression															
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	444.28	199.12	68.55	4.26	5.25	721.46	Predict	NSR	62%	28%	10%	1%	1%	100%
	LSR	110.59	160.86	88.58	9.82	11.55	381.40		LSR	29%	42%	23%	3%	3%	100%
	MSR	16.93	29.12	28.98	4.17	3.94	83.14		MSR	20%	35%	35%	5%	5%	100%
	HSR	0.25	1.12	0.61	0.38	0.16	2.52		HSR	10%	44%	24%	15%	6%	100%
	ISR	0.95	0.78	1.28	0.37	1.10	4.48		ISR	21%	17%	29%	8%	25%	100%
	TTL	573.00	391.00	188.00	19.00	22.00	1193.00		TTL	48%	33%	16%	2%	2%	100%
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	37%	17%	6%	0%	0%	60%	Predict	NSR	78%	51%	36%	22%	24%	60%
	LSR	9%	13%	7%	1%	1%	32%		LSR	19%	41%	47%	52%	53%	32%
	MSR	1%	2%	2%	0%	0%	7%		MSR	3%	7%	15%	22%	18%	7%
	HSR	0%	0%	0%	0%	0%	0%		HSR	0%	0%	0%	2%	1%	0%
	ISR	0%	0%	0%	0%	0%	0%		ISR	0%	0%	1%	2%	5%	0%
	TTL	48%	33%	16%	2%	2%	100%		TTL	100%	100%	100%	100%	100%	100%
Testing Error		46.72%		Sen	30.86%	Spe	77.54%	FP/FN		22.46%	58.86%	84.59%	98.00%	95.00%	69.14%

4.Multinomial Regression + Bagging															
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	436.00	202.00	65.00	4.00	4.00	711.00	Predict	NSR	61%	28%	9%	1%	1%	100%
	LSR	115.00	159.00	88.00	9.00	11.00	382.00		LSR	30%	42%	23%	2%	3%	100%
	MSR	22.00	29.00	33.00	4.00	4.00	92.00		MSR	24%	32%	36%	4%	4%	100%
	HSR	0.00	0.00	0.00	1.00	0.00	1.00		HSR	0%	0%	0%	100%	0%	100%
	ISR	0.00	1.00	2.00	1.00	3.00	7.00		ISR	0%	14%	29%	14%	43%	100%
	TTL	573.00	391.00	188.00	19.00	22.00	1193.00		TTL	48%	33%	16%	2%	2%	100%
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	37%	17%	5%	0%	0%	60%	Predict	NSR	76%	52%	35%	21%	18%	60%
	LSR	10%	13%	7%	1%	1%	32%		LSR	20%	41%	47%	47%	50%	32%
	MSR	2%	2%	3%	0%	0%	8%		MSR	4%	7%	18%	21%	18%	8%
	HSR	0%	0%	0%	0%	0%	0%		HSR	0%	0%	0%	5%	0%	0%
	ISR	0%	0%	0%	0%	0%	1%		ISR	0%	0%	1%	5%	14%	1%
	TTL	48%	33%	16%	2%	2%	100%		TTL	100%	100%	100%	100%	100%	100%
Testing Error		47.02%		Sen	31.61%	Spe	76.09%	FP/FN		23.91%	59.34%	82.45%	94.74%	86.36%	68.39%

Figure 21: Confusion Matrix- Multinomial Outcome 02

5.Decision Tree

		TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	491.50	276.63	104.88	9.88	12.89	895.78
	LSR	81.50	114.37	83.12	9.12	9.11	297.22
	MSR	0.00	0.00	0.00	0.00	0.00	0.00
	HSR	0.00	0.00	0.00	0.00	0.00	0.00
	ISR	0.00	0.00	0.00	0.00	0.00	0.00
	TTL	573.00	391.00	188.00	19.00	22.00	1193.00

		TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	55%	31%	12%	1%	1%	100%
	LSR	27%	38%	28%	3%	3%	100%
	MSR	0%	0%	0%	0%	0%	100%
	HSR	0%	0%	0%	0%	0%	100%
	ISR	0%	0%	0%	0%	0%	100%
	TTL	48%	33%	16%	2%	2%	100%

		TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	41%	23%	9%	1%	1%	75%
	LSR	7%	10%	7%	1%	1%	25%
	MSR	0%	0%	0%	0%	0%	0%
	HSR	0%	0%	0%	0%	0%	0%
	ISR	0%	0%	0%	0%	0%	0%
	TTL	48%	33%	16%	2%	2%	100%
Testing Error		49.21%		Sen	18.45%	Spe	85.78%

		TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	86%	71%	56%	52%	59%	75%
	LSR	14%	29%	44%	48%	41%	25%
	MSR	0%	0%	0%	0%	0%	0%
	HSR	0%	0%	0%	0%	0%	0%
	ISR	0%	0%	0%	0%	0%	0%
	TTL	100%	100%	100%	100%	100%	100%
FP/FN		14.22%	70.75%	######	######	######	81.55%

6.Bagging

		TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	431.49	173.52	54.72	4.29	6.84	670.86
	LSR	114.44	165.14	83.96	8.94	8.25	380.73
	MSR	25.63	49.08	46.30	4.38	4.80	130.19
	HSR	0.45	1.55	1.26	0.68	0.61	4.55
	ISR	0.99	1.71	1.76	0.71	1.50	6.67
	TTL	573.00	391.00	188.00	19.00	22.00	1193.00

		TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	64%	26%	8%	1%	1%	100%
	LSR	30%	43%	22%	2%	2%	100%
	MSR	20%	38%	36%	3%	4%	100%
	HSR	10%	34%	28%	15%	13%	100%
	ISR	15%	26%	26%	11%	22%	100%
	TTL	48%	33%	16%	2%	2%	100%

		TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	36%	15%	5%	0%	1%	56%
	LSR	10%	14%	7%	1%	1%	32%
	MSR	2%	4%	4%	0%	0%	11%
	HSR	0%	0%	0%	0%	0%	0%
	ISR	0%	0%	0%	0%	0%	1%
	TTL	48%	33%	16%	2%	2%	100%
Testing Error		45.93%		Sen	34.45%	Spe	75.30%

		TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	75%	44%	29%	23%	31%	56%
	LSR	20%	42%	45%	47%	38%	32%
	MSR	4%	13%	25%	23%	22%	11%
	HSR	0%	0%	1%	4%	3%	0%
	ISR	0%	0%	1%	4%	7%	1%
	TTL	100%	100%	100%	100%	100%	100%
FP/FN		24.70%	57.76%	75.37%	96.42%	93.18%	65.55%

Figure 22: Confusion Matrix- Multinomial Outcome 03

7.Random Forest															
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	450.19	178.20	54.28	4.30	6.15	693.12	Predict	NSR	65%	26%	8%	1%	1%	100%
	LSR	102.39	170.09	88.41	9.32	8.44	378.65		LSR	27%	45%	23%	2%	2%	100%
	MSR	19.10	39.72	43.07	4.56	5.10	111.55		MSR	17%	36%	39%	4%	5%	100%
	HSR	0.22	1.04	0.63	0.17	0.19	2.25		HSR	10%	46%	28%	8%	8%	100%
	ISR	1.10	1.95	1.61	0.65	2.12	7.43		ISR	15%	26%	22%	9%	29%	100%
	TTL	573.00	391.00	188.00	19.00	22.00	1193.00		TTL	48%	33%	16%	2%	2%	100%
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	38%	15%	5%	0%	1%	58%	Predict	NSR	79%	46%	29%	23%	28%	58%
	LSR	9%	14%	7%	1%	1%	32%		LSR	18%	44%	47%	49%	38%	32%
	MSR	2%	3%	4%	0%	0%	9%		MSR	3%	10%	23%	24%	23%	9%
	HSR	0%	0%	0%	0%	0%	0%		HSR	0%	0%	0%	1%	1%	0%
	ISR	0%	0%	0%	0%	0%	1%		ISR	0%	0%	1%	3%	10%	1%
	TTL	48%	33%	16%	2%	2%	100%		TTL	100%	100%	100%	100%	100%	100%
Testing Error		44.20%		Sen	34.75%	Spe	78.57%	FP/FN		21.43%	56.50%	77.09%	99.11%	90.36%	65.25%

8.Boosting															
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	432.40	173.49	55.58	4.31	5.64	671.42	Predict	NSR	64%	26%	8%	1%	1%	100%
	LSR	113.20	167.43	83.99	8.61	9.27	382.50		LSR	30%	44%	22%	2%	2%	100%
	MSR	24.44	43.52	42.30	4.48	4.45	119.19		MSR	21%	37%	35%	4%	4%	100%
	HSR	1.24	3.23	2.44	0.76	0.63	8.30		HSR	15%	39%	29%	9%	8%	100%
	ISR	1.72	3.33	3.69	0.84	2.01	11.59		ISR	15%	29%	32%	7%	17%	100%
	TTL	573.00	391.00	188.00	19.00	22.00	1193.00		TTL	48%	33%	16%	2%	2%	100%
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	36%	15%	5%	0%	0%	56%	Predict	NSR	75%	44%	30%	23%	26%	56%
	LSR	9%	14%	7%	1%	1%	32%		LSR	20%	43%	45%	45%	42%	32%
	MSR	2%	4%	4%	0%	0%	10%		MSR	4%	11%	23%	24%	20%	10%
	HSR	0%	0%	0%	0%	0%	1%		HSR	0%	1%	1%	4%	3%	1%
	ISR	0%	0%	0%	0%	0%	1%		ISR	0%	1%	2%	4%	9%	1%
	TTL	48%	33%	16%	2%	2%	100%		TTL	100%	100%	100%	100%	100%	100%
Testing Error		45.94%		Sen	34.27%	Spe	75.46%	FP/FN		24.54%	57.18%	77.50%	96.00%	90.86%	65.73%

Figure 23: Confusion Matrix- Multinomial Outcome 04

[Undersampling - Simple Random Sampling] maintain same scale of sample size of minority group- Bagging															
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	10.05	5.40	3.26	0.79	1.00	20.50	Predict	NSR	49%	26%	16%	4%	5%	100%
	LSR	4.64	5.60	3.94	1.35	1.28	16.81		LSR	28%	33%	23%	8%	8%	100%
	MSR	2.97	4.71	7.07	2.40	1.97	19.12		MSR	16%	25%	37%	13%	10%	100%
	HSR	1.16	2.41	3.17	13.87	1.86	22.47		HSR	5%	11%	14%	62%	8%	100%
	ISR	1.18	1.88	2.56	1.59	13.89	21.10		ISR	6%	9%	12%	8%	66%	100%
	TTL	20.00	20.00	20.00	20.00	20.00	100.00		TTL	20%	20%	20%	20%	20%	100%
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	10%	5%	3%	1%	1%	21%	Predict	NSR	50%	27%	16%	4%	5%	21%
	LSR	5%	6%	4%	1%	1%	17%		LSR	23%	28%	20%	7%	6%	17%
	MSR	3%	5%	7%	2%	2%	19%		MSR	15%	24%	35%	12%	10%	19%
	HSR	1%	2%	3%	14%	2%	22%		HSR	6%	12%	16%	69%	9%	22%
	ISR	1%	2%	3%	2%	14%	21%		ISR	6%	9%	13%	8%	69%	21%
	TTL	20%	20%	20%	20%	20%	100%		TTL	100%	100%	100%	100%	100%	100%
Testing Error		49.52%		Sen	50.54%	Spe	50.25%	FP/FN		49.75%	72.00%	64.65%	30.65%	30.55%	49.46%

[Undersampling - Simple Random Sampling] maintain same scale of sample size of minority group- Boosting															
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	8.93	5.04	3.29	0.84	0.94	19.04	Predict	NSR	47%	26%	17%	4%	5%	100%
	LSR	4.74	5.90	4.19	1.40	1.43	17.66		LSR	27%	33%	24%	8%	8%	100%
	MSR	3.50	4.48	6.49	2.23	2.14	18.84		MSR	19%	24%	34%	12%	11%	100%
	HSR	1.22	2.42	3.13	13.77	1.92	22.46		HSR	5%	11%	14%	61%	9%	100%
	ISR	1.61	2.16	2.90	1.76	13.57	22.00		ISR	7%	10%	13%	8%	62%	100%
	TTL	20.00	20.00	20.00	20.00	20.00	100.00		TTL	20%	20%	20%	20%	20%	100%
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	9%	5%	3%	1%	1%	19%	Predict	NSR	45%	25%	16%	4%	5%	19%
	LSR	5%	6%	4%	1%	1%	18%		LSR	24%	30%	21%	7%	7%	18%
	MSR	4%	4%	6%	2%	2%	19%		MSR	18%	22%	32%	11%	11%	19%
	HSR	1%	2%	3%	14%	2%	22%		HSR	6%	12%	16%	69%	10%	22%
	ISR	2%	2%	3%	2%	14%	22%		ISR	8%	11%	15%	9%	68%	22%
	TTL	20%	20%	20%	20%	20%	100%		TTL	100%	100%	100%	100%	100%	100%
Testing Error		51.34%		Sen	49.66%	Spe	44.65%	FP/FN		55.35%	70.50%	67.55%	31.15%	32.15%	50.34%

Figure 24: Undersampling - Simple Random Sampling

[Undersampling -SMOTE] maintain same scale of sample size of minority group- Bagging															
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	10.62	5.01	2.69	1.23	0.84	20.39	Predict	NSR	52%	25%	13%	6%	4%	100%
	LSR	4.51	5.67	3.92	2.05	1.92	18.07		LSR	25%	31%	22%	11%	11%	100%
	MSR	2.75	4.69	7.24	2.42	2.22	19.32		MSR	14%	24%	37%	13%	11%	100%
	HSR	1.16	2.55	3.31	12.62	2.36	22.00		HSR	5%	12%	15%	57%	11%	100%
	ISR	0.96	2.08	2.84	1.68	12.66	20.22		ISR	5%	10%	14%	8%	63%	100%
	TTL	20.00	20.00	20.00	20.00	20.00	100.00		TTL	20%	20%	20%	20%	20%	100%
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	11%	5%	3%	1%	1%	20%	Predict	NSR	53%	25%	13%	6%	4%	20%
	LSR	5%	6%	4%	2%	2%	18%		LSR	23%	28%	20%	10%	10%	18%
	MSR	3%	5%	7%	2%	2%	19%		MSR	14%	23%	36%	12%	11%	19%
	HSR	1%	3%	3%	13%	2%	22%		HSR	6%	13%	17%	63%	12%	22%
	ISR	1%	2%	3%	2%	13%	20%		ISR	5%	10%	14%	8%	63%	20%
	TTL	20%	20%	20%	20%	20%	100%		TTL	100%	100%	100%	100%	100%	100%
Testing Error		51.19%		Sen	47.74%	Spe	53.10%	FP/FN		46.90%	71.65%	63.80%	36.90%	36.70%	52.26%

[Undersampling -SMOTE] maintain same scale of sample size of minority group- Boosting															
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	9.32	4.79	3.11	1.09	1.19	19.50	Predict	NSR	48%	25%	16%	6%	6%	100%
	LSR	4.93	6.01	3.74	2.14	1.99	18.81		LSR	26%	32%	20%	11%	11%	100%
	MSR	3.10	4.25	6.46	2.54	2.28	18.63		MSR	17%	23%	35%	14%	12%	100%
	HSR	1.18	2.41	3.34	12.37	2.15	21.45		HSR	6%	11%	16%	58%	10%	100%
	ISR	1.47	2.54	3.35	1.86	12.39	21.61		ISR	7%	12%	16%	9%	57%	100%
	TTL	20.00	20.00	20.00	20.00	20.00	100.00		TTL	20%	20%	20%	20%	20%	100%
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	9%	5%	3%	1%	1%	20%	Predict	NSR	47%	24%	16%	5%	6%	20%
	LSR	5%	6%	4%	2%	2%	19%		LSR	25%	30%	19%	11%	10%	19%
	MSR	3%	4%	6%	3%	2%	19%		MSR	16%	21%	32%	13%	11%	19%
	HSR	1%	2%	3%	12%	2%	21%		HSR	6%	12%	17%	62%	11%	21%
	ISR	1%	3%	3%	2%	12%	22%		ISR	7%	13%	17%	9%	62%	22%
	TTL	20%	20%	20%	20%	20%	100%		TTL	100%	100%	100%	100%	100%	100%
Testing Error		53.45%		Sen	46.54%	Spe	46.60%	FP/FN		53.40%	69.95%	67.70%	38.15%	38.05%	53.46%

Figure 25: Undersampling - SMOTE

[Oversampling - Simple Random Sampling] 5 times sample size of minority group- Bagging															
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	62.89	23.08	10.10	0.17	0.37	96.61	Predict	NSR	65%	24%	10%	0%	0%	100%
	LSR	19.96	44.19	17.79	0.52	0.50	82.96		LSR	24%	53%	21%	1%	1%	100%
	MSR	12.42	23.35	60.24	0.68	1.12	97.81		MSR	13%	24%	62%	1%	1%	100%
	HSR	2.15	4.95	5.73	97.15	2.96	112.94		HSR	2%	4%	5%	86%	3%	100%
	ISR	2.58	4.43	6.14	1.48	95.05	109.68		ISR	2%	4%	6%	1%	87%	100%
	TTL	100.00	100.00	100.00	100.00	100.00	500.00		TTL	20%	20%	20%	20%	20%	100%
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	13%	5%	2%	0%	0%	19%	Predict	NSR	63%	23%	10%	0%	0%	19%
	LSR	4%	9%	4%	0%	0%	17%		LSR	20%	44%	18%	1%	1%	17%
	MSR	2%	5%	12%	0%	0%	20%		MSR	12%	23%	60%	1%	1%	20%
	HSR	0%	1%	1%	19%	1%	23%		HSR	2%	5%	6%	97%	3%	23%
	ISR	1%	1%	1%	0%	19%	22%		ISR	3%	4%	6%	1%	95%	22%
	TTL	20%	20%	20%	20%	20%	100%		TTL	100%	100%	100%	100%	100%	100%
Testing Error		**28.10%**		**Sen**	**74.16%**	**Spe**	**62.89%**	**FP/FN**		**37.11%**	**55.81%**	**39.76%**	**2.85%**	**4.95%**	**25.84%**

[Oversampling - Simple Random Sampling] 5 times sample size of minority group- Boosting															
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	58.86	23.97	11.65	0.44	0.69	95.61	Predict	NSR	62%	25%	12%	0%	1%	100%
	LSR	21.99	43.01	19.91	0.95	1.19	87.05		LSR	25%	49%	23%	1%	1%	100%
	MSR	12.96	21.67	52.55	1.06	1.88	90.12		MSR	14%	24%	58%	1%	2%	100%
	HSR	2.51	5.25	7.24	95.46	2.79	113.25		HSR	2%	5%	6%	84%	2%	100%
	ISR	3.68	6.10	8.65	2.09	93.45	113.97		ISR	3%	5%	8%	2%	82%	100%
	TTL	100.00	100.00	100.00	100.00	100.00	500.00		TTL	20%	20%	20%	20%	20%	100%
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	12%	5%	2%	0%	0%	19%	Predict	NSR	59%	24%	12%	0%	1%	19%
	LSR	4%	9%	4%	0%	0%	17%		LSR	22%	43%	20%	1%	1%	17%
	MSR	3%	4%	11%	0%	0%	18%		MSR	13%	22%	53%	1%	2%	18%
	HSR	1%	1%	1%	19%	1%	23%		HSR	3%	5%	7%	95%	3%	23%
	ISR	1%	1%	2%	0%	19%	23%		ISR	4%	6%	9%	2%	93%	23%
	TTL	20%	20%	20%	20%	20%	100%		TTL	100%	100%	100%	100%	100%	100%
Testing Error		**31.33%**		**Sen**	**71.12%**	**Spe**	**58.86%**	**FP/FN**		**41.14%**	**56.99%**	**47.45%**	**4.54%**	**6.55%**	**28.88%**

Figure 26: Oversampling - Simple Random Sampling - 5 times

[Oversampling - SMOTE] 5 times sample size of minority group- Bagging															
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	62.91	22.81	9.70	0.23	0.31	95.96	Predict	NSR	65%	24%	10%	0%	0%	99%
	LSR	19.93	44.12	19.79	0.38	0.66	84.88		LSR	24%	53%	24%	0%	1%	102%
	MSR	12.57	24.17	57.91	0.83	1.72	97.20		MSR	13%	25%	59%	1%	2%	99%
	HSR	2.25	4.77	6.34	97.32	3.28	113.96		HSR	2%	4%	6%	86%	3%	101%
	ISR	2.34	4.13	6.26	1.24	94.03	108.00		ISR	2%	4%	6%	1%	86%	98%
	TTL	100.00	100.00	100.00	100.00	100.00	500.00		TTL	20%	20%	20%	20%	20%	100%
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	13%	5%	2%	0%	0%	19%	Predict	NSR	63%	23%	10%	0%	0%	19%
	LSR	4%	9%	4%	0%	0%	17%		LSR	20%	44%	20%	0%	1%	17%
	MSR	3%	5%	12%	0%	0%	19%		MSR	13%	24%	58%	1%	2%	19%
	HSR	0%	1%	1%	19%	1%	23%		HSR	2%	5%	6%	97%	3%	23%
	ISR	0%	1%	1%	0%	19%	22%		ISR	2%	4%	6%	1%	94%	22%
	TTL	20%	20%	20%	20%	20%	100%		TTL	100%	100%	100%	100%	100%	100%
Testing Error		28.74%		Sen	73.35%	Spe	62.91%	FP/FN		37.09%	55.88%	42.09%	2.68%	5.97%	26.66%

[Oversampling - SMOTE] 5 times sample size of minority group- Boosting															
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	58.92	23.04	10.74	0.36	0.83	93.89	Predict	NSR	62%	24%	11%	0%	1%	98%
	LSR	22.20	41.50	20.85	0.73	1.21	86.49		LSR	26%	48%	24%	1%	1%	99%
	MSR	12.76	23.20	51.36	1.13	2.44	90.89		MSR	14%	26%	57%	1%	3%	101%
	HSR	2.57	6.22	8.02	96.19	2.93	115.93		HSR	2%	5%	7%	85%	3%	102%
	ISR	3.55	6.04	9.03	1.59	92.59	112.80		ISR	3%	5%	8%	1%	81%	99%
	TTL	100.00	100.00	100.00	100.00	100.00	500.00		TTL	20%	20%	20%	20%	20%	100%
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	12%	5%	2%	0%	0%	19%	Predict	NSR	59%	23%	11%	0%	1%	19%
	LSR	4%	8%	4%	0%	0%	17%		LSR	22%	42%	21%	1%	1%	17%
	MSR	3%	5%	10%	0%	0%	18%		MSR	13%	23%	51%	1%	2%	18%
	HSR	1%	1%	2%	19%	1%	23%		HSR	3%	6%	8%	96%	3%	23%
	ISR	1%	1%	2%	0%	19%	23%		ISR	4%	6%	9%	2%	93%	23%
	TTL	20%	20%	20%	20%	20%	100%		TTL	100%	100%	100%	100%	100%	100%
Testing Error		31.89%		Sen	70.41%	Spe	58.92%	FP/FN		41.08%	58.50%	48.64%	3.81%	7.41%	29.59%

Figure 27: Oversampling - SMOTE - 5 times

[Oversampling - Simple Random Sampling] 10 times sample size of minority group- Bagging															
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	139.71	38.00	14.38	0.03	0.03	192.15	Predict	NSR	73%	20%	7%	0%	0%	100%
	LSR	35.61	115.59	26.08	0.03	0.14	177.45		LSR	20%	65%	15%	0%	0%	100%
	MSR	19.64	36.92	145.93	0.12	0.39	203.00		MSR	10%	18%	72%	0%	0%	100%
	HSR	1.88	4.55	5.54	197.52	5.16	214.65		HSR	1%	2%	3%	92%	2%	100%
	ISR	3.16	4.94	8.07	2.30	194.28	212.75		ISR	1%	2%	4%	1%	91%	100%
	TTL	200.00	200.00	200.00	200.00	200.00	1000.00		TTL	20%	20%	20%	20%	20%	100%
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	14%	4%	1%	0%	0%	19%	Predict	NSR	70%	19%	7%	0%	0%	19%
	LSR	4%	12%	3%	0%	0%	18%		LSR	18%	58%	13%	0%	0%	18%
	MSR	2%	4%	15%	0%	0%	20%		MSR	10%	18%	73%	0%	0%	20%
	HSR	0%	0%	1%	20%	1%	21%		HSR	1%	2%	3%	99%	3%	21%
	ISR	0%	0%	1%	0%	19%	21%		ISR	2%	2%	4%	1%	97%	21%
	TTL	20%	20%	20%	20%	20%	100%		TTL	100%	100%	100%	100%	100%	100%
Testing Error		20.70%		Sen	81.67%	Spe	69.86%	FP/FN		30.15%	42.21%	27.04%	1.24%	2.86%	18.34%

[Oversampling - Simple Random Sampling] 10 times sample size of minority group- Boosting															
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	124.92	42.34	19.51	0.29	0.28	187.34	Predict	NSR	67%	23%	10%	0%	0%	100%
	LSR	40.85	96.57	33.96	0.34	0.68	172.40		LSR	24%	56%	20%	0%	0%	100%
	MSR	23.45	42.76	119.00	0.63	1.49	187.33		MSR	13%	23%	64%	0%	1%	100%
	HSR	4.51	8.47	11.96	195.70	4.76	225.40		HSR	2%	4%	5%	87%	2%	100%
	ISR	6.27	9.86	15.57	3.04	192.79	227.53		ISR	3%	4%	7%	1%	85%	100%
	TTL	200.00	200.00	200.00	200.00	200.00	1000.00		TTL	20%	20%	20%	20%	20%	100%
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	12%	4%	2%	0%	0%	19%	Predict	NSR	62%	21%	10%	0%	0%	19%
	LSR	4%	10%	3%	0%	0%	17%		LSR	20%	48%	17%	0%	0%	17%
	MSR	2%	4%	12%	0%	0%	19%		MSR	12%	21%	60%	0%	1%	19%
	HSR	0%	1%	1%	20%	0%	23%		HSR	2%	4%	6%	98%	2%	23%
	ISR	1%	1%	2%	0%	19%	23%		ISR	3%	5%	8%	2%	96%	23%
	TTL	20%	20%	20%	20%	20%	100%		TTL	100%	100%	100%	100%	100%	100%
Testing Error		27.10%		Sen	75.51%	Spe	62.46%	FP/FN		37.54%	51.72%	40.50%	2.15%	3.61%	24.49%

Figure 28: Oversampling - Simple Random Sampling - 10 times

[Oversampling - SMOTE] 10 times sample size of minority group- Bagging															
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	137.70	41.02	15.77	0.00	0.06	194.55	Predict	NSR	72%	21%	8%	0%	0%	101%
	LSR	37.09	109.12	31.76	0.00	0.01	177.98		LSR	21%	61%	18%	0%	0%	100%
	MSR	20.22	40.28	137.96	0.09	0.89	199.44		MSR	10%	20%	68%	0%	0%	98%
	HSR	2.08	5.09	6.64	197.11	5.12	216.04		HSR	1%	2%	3%	92%	2%	101%
	ISR	2.91	4.49	7.87	2.80	193.92	211.99		ISR	1%	2%	4%	1%	91%	100%
	TTL	200.00	200.00	200.00	200.00	200.00	1000.00		TTL	20%	20%	20%	20%	20%	100%
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	14%	4%	2%	0%	0%	19%	Predict	NSR	69%	21%	8%	0%	0%	19%
	LSR	4%	11%	3%	0%	0%	18%		LSR	19%	55%	16%	0%	0%	18%
	MSR	2%	4%	14%	0%	0%	20%		MSR	10%	20%	69%	0%	0%	20%
	HSR	0%	1%	1%	20%	1%	22%		HSR	1%	3%	3%	99%	3%	22%
	ISR	0%	0%	1%	0%	19%	21%		ISR	1%	2%	4%	1%	97%	21%
	TTL	20%	20%	20%	20%	20%	100%		TTL	100%	100%	100%	100%	100%	100%
Testing Error		22.42%		Sen	79.76%	Spe	68.85%	FP/FN		31.15%	45.44%	31.02%	1.45%	3.04%	20.24%

[Oversampling - SMOTE] 10 times sample size of minority group- Boosting															
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	124.97	44.76	19.49	0.16	0.57	189.95	Predict	NSR	67%	24%	10%	0%	0%	101%
	LSR	41.31	90.88	37.27	0.25	0.58	170.29		LSR	24%	53%	22%	0%	0%	99%
	MSR	22.66	45.36	114.56	0.33	2.70	185.61		MSR	12%	24%	61%	0%	1%	99%
	HSR	4.06	8.82	13.15	196.00	4.93	226.96		HSR	2%	4%	6%	87%	2%	101%
	ISR	7.00	10.18	15.53	3.26	191.22	227.19		ISR	3%	4%	7%	1%	84%	100%
	TTL	200.00	200.00	200.00	200.00	200.00	1000.00		TTL	20%	20%	20%	20%	20%	100%
		TRUE								TRUE					
		NSR	LSR	MSR	HSR	ISR	TTL			NSR	LSR	MSR	HSR	ISR	TTL
Predict	NSR	12%	4%	2%	0%	0%	19%	Predict	NSR	62%	22%	10%	0%	0%	19%
	LSR	4%	9%	4%	0%	0%	17%		LSR	21%	45%	19%	0%	0%	17%
	MSR	2%	5%	11%	0%	0%	19%		MSR	11%	23%	57%	0%	1%	19%
	HSR	0%	1%	1%	20%	0%	23%		HSR	2%	4%	7%	98%	2%	23%
	ISR	1%	1%	2%	0%	19%	23%		ISR	4%	5%	8%	2%	96%	23%
	TTL	20%	20%	20%	20%	20%	100%		TTL	100%	100%	100%	100%	100%	100%
Testing Error		28.24%		Sen	74.08%	Spe	62.49%	FP/FN		37.52%	54.56%	42.72%	2.00%	4.39%	25.92%

Figure 29: Oversampling - SMOTE - 10 times

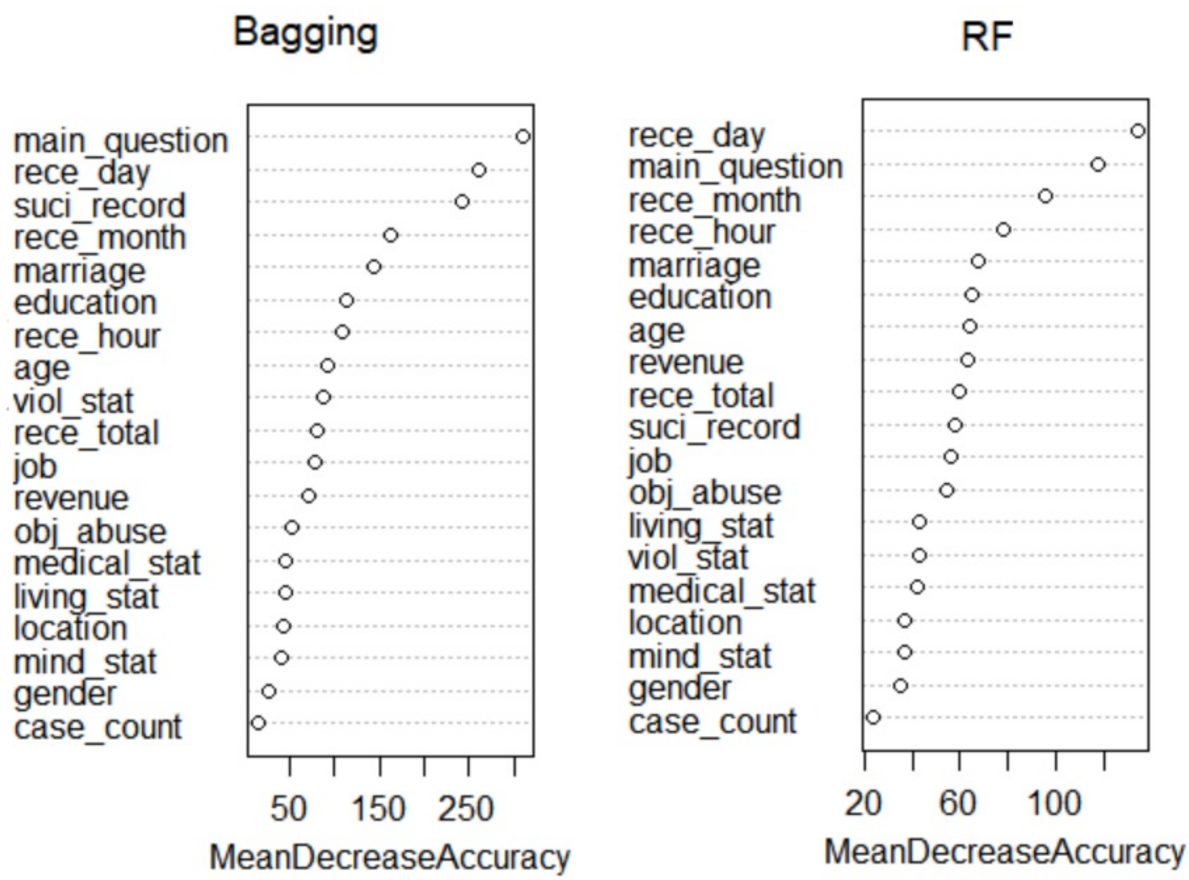

Figure 30: Variable Importance