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Machine Learning Based Suicide Ideation Prediction for Military Personnel

Mrs R Jhansi Rani MCA [1], Manchinti Pavan Kumar Reddy [2]

[1] Asst. Professor, Department Computer Applications
[2] Student, Department of Computer Applications
[1], [2] Chadalawada Ramanamma Engineering College (Autonomous)

ABSTRACT

Military personnel have greater psychological stress and are at higher suicide attempt risk compared with the general population. High mental stress may cause suicide ideations which are crucially driving suicide attempts. However, traditional statistical methods could only find a moderate degree of correlation between psychological stress and suicide ideation in non-psychiatric individuals. This project utilizes machine learning techniques including logistic regression, decision tree, random forest, gradient boosting regression tree, support vector machine and multilayer perceptron to predict the presence of suicide ideation by six important psychological stress domains of the military males and females. The accuracies of all the six machine learning methods are over 98%. Among them, the multilayer perceptron and support vector machine provide the best predictions of suicide ideation approximately to 100%. As compared with the BSRS-5 score ≥ 7, a conventional criterion, for the presence of suicide ideation ≥ 1, the proposed algorithms can improve the performances of accuracy, sensitivity, specificity, precision, the AUC of ROC curve and the AUC of PR curve up to 5.7%, 35.9%, 4.6%, 65.2%, 4.3% and 53.2%, respectively; and for the presence of more severely intense suicide ideation ≥ 2, the improvements are 6.1%, 26.2%, 5.8%, 83.5%, 2.8% and 64.7%, respectively.

Keywords: - Military personnel, Machine Learning, Accuracy, Improvements, Support Vector Machine.

I. INTRODUCTION

This project utilizes machine learning techniques including logistic regression, decision tree, random forest, gradient boosting regression tree, support vector machine and multilayer perceptron to predict the presence of suicide ideation. Most nonfatal suicide attempts and suicide deaths occur among patients who deny suicidal ideation (SI) during suicide risk screenings. Little is known about risk factors for suicidal behaviors among such patients. We investigated this in a representative sample of U.S. Army soldiers who denied lifetime SI in a survey and were then followed through administrative records for up to 45 months to learn of administratively-recorded suicide attempts (SA). A novel two-stage risk assessment approach was used that combined first stage prediction from administrative records to find the subsample of SI deniers with highest subsequent SA risk and then used survey reports to estimate a second-stage model identifying the subset of individuals in the high-risk subsample at highest SA risk. 70% of survey respondents denied lifetime SI. Administrative data identified 30% of this 70% who accounted for 81.2% of subsequent administratively-recorded SAs. A relatively small number of self-report survey variables were then used to create a prediction model that identified 10% of the first-stage high-risk sample (i.e., 3% of all soldiers) at highest SA risk (accounting for 45% of SAs in the total sample). We close by discussing potential applications of this approach for identifying future SI deniers at highest SA risk. In the existing work, the system is not Characterizing High mental stress which may cause suicide ideations which are crucially driving suicide attempts. This system does not aim to find behavioral characteristics of suicide attempters.

II. RELATEDWORKS

MILITARY personnel are vulnerable to psychological stress because of tense physical training, multiple deployments and responsibilities. The prevalence of major depression was reported, ranging from 2.0% to 37.4% in the US military [1], and that of combat-related posttraumatic stress disorder (PTSD) was reported 2.0%-17.0% among

US military war veterans [2]. A meta-analysis showed consistent results that the worldwide pooled prevalence of PTSD in rescue workers was up to 10.0% [3]. The symptoms of mental disorders developed frequently in those of continued combat exposure and those of repeated deployments [4]. The association between military absenteeism and mental health problems has been discussed in [5]. The rate of suicide attempt among active duty US Army personnel has been increasingly higher than that in the civilians [6]. According to an analysis for 27,501 military participants in [7], 14.3% of survey respondents reported suicide ideation and 3.0% committed suicide. In other words, 21% of those with suicide ideation had suicide attempt. As is known, previous studies have revealed a relationship between suicide ideation and psychological stress [8],[9]. To early predict the presence of suicide ideation and further prevent the behavior of suicide are essential and important in the military. With the technology improvement and the availability of various kinds of real world big data, artificial intelligence (AI) grows fast accordingly. The academics have made great efforts on the computerized algorithms to deal with big data. Machine learning, a combination of AI and computations, could provide accurate diagnosis of diseases and predict the outcomes [10]-[17]. For instance, the circuits for seizure classification and detection by machine learning are implemented in [18]. Recognition of heart murmurs could be achieved by deep neural networks [19]. In addition, Ambale-Venkatesh *et al.* identified the top-20 risk factors of incident cardiovascular events by the random survival forest which performance was better than the conventional risk calculators [20]. Therefore, using machine learning and deep learning techniques has become an efficient and reliable tool for clinical practice by physicians globally. High mental stress may cause suicide ideations which are crucially driving suicide attempts. However, traditional statistical methods find merely a moderate correlation between psychological stress and suicide ideation. Machine learning could provide better performance of the prediction of suicide ideations. In this paper, we utilize a large sample of the military members for several machine learning techniques by taking the psychological stress dimensions into consideration to predict the presence of suicide ideation. The schematic diagram of the proposed method in this paper is illustrated in Fig. 1. A binary probabilistic classifier of machine learning algorithm can determine whether the military persons, through their questionnaires, have suicide ideations. Machine learning provides an effective manner for early warning and prevention of suicide by automatic suicide ideation detection.

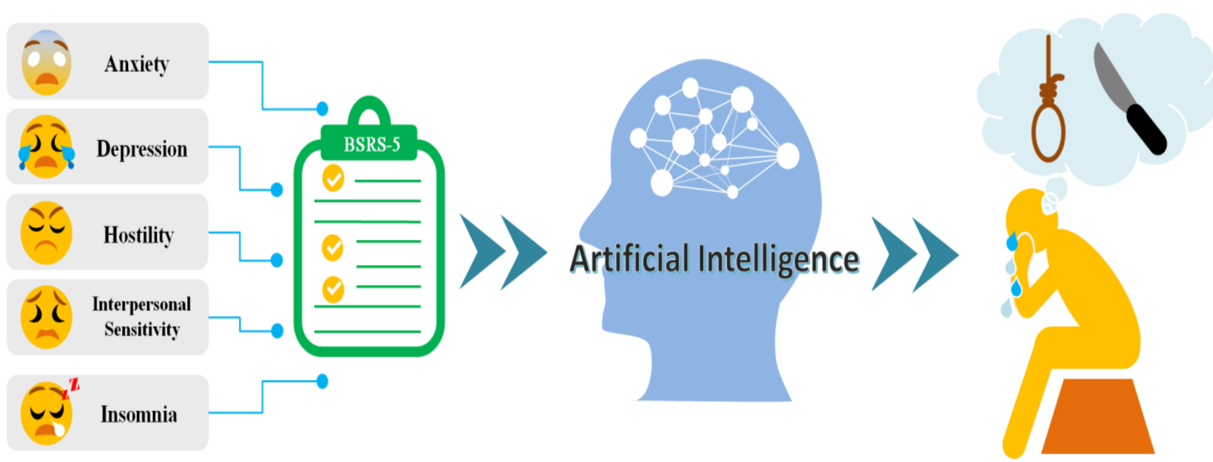


Fig.1 Schematic diagram of proposed method

III. PROPOSED SYSTEM ARCHITECTURE

Gradient boosting decision tree (GBDT) is also an ensemble machine learning method and constructs multiple additive decision tree models. The DTs fitting the gradient on pseudo residuals of previous cumulative models are repeatedly trained to minimize mean squared error. This sequential stepwise manner combines the performance of weak learners (i.e., DT here) in an iterative fashion into a single strong learner to increase the accuracy of prediction. Our algorithm uses the maximum tree depth as the hyper parameter to be optimized to avoid over-fitting. Support vector machine (SVM) with linear kernel (Linear SVM) is used for our proposed method. A data point is viewed as a 6-dimensional vector and we separate such points with a hyperplane. This linear SVM constructs the maximum-margin hyperplane so that the distance from it to the nearest training data point of any class (class 0 or class 1) is maximized. Random forest (RF) an ensemble machine learning technique, constructs multiple decision trees and collects them together for classification. The training algorithm adopted in our method for random forest is the bootstrap aggregating (bagging) technique. RF builds multiple CART models with different samples and different initial variables. In each decision tree, a random subset of the features is taken into consideration for splitting a node. The individual trees are not correlated with each other and thus the trees in random forest of our method are not pruned. The final prediction result is according to the majority-votes model from the multiple DTs. RF combines the merits of feature selection and bagging. The decision tree number is the hyper parameter to be optimized. In the proposed system, the academics have made great efforts on the computerized algorithms to deal with big data of suicide attempts. The system is more powerful in finding both Psychological Stress, Suicide Ideation. The six input factors of psychological stress for machine learning include BSRS-5 score, anxiety, depression, hostility, interpersonal sensitivity and insomnia. This paper uses six machine learning techniques including logistic regression (LR), decision tree (DT), random forest (RF), gradient boosting decision tree (GBDT), support vector machine (SVM) and multilayer perceptron (MLP) for the prediction of the presence of suicide ideation of the military members. The system diagram of proposed method is illustrated in Fig. 2.

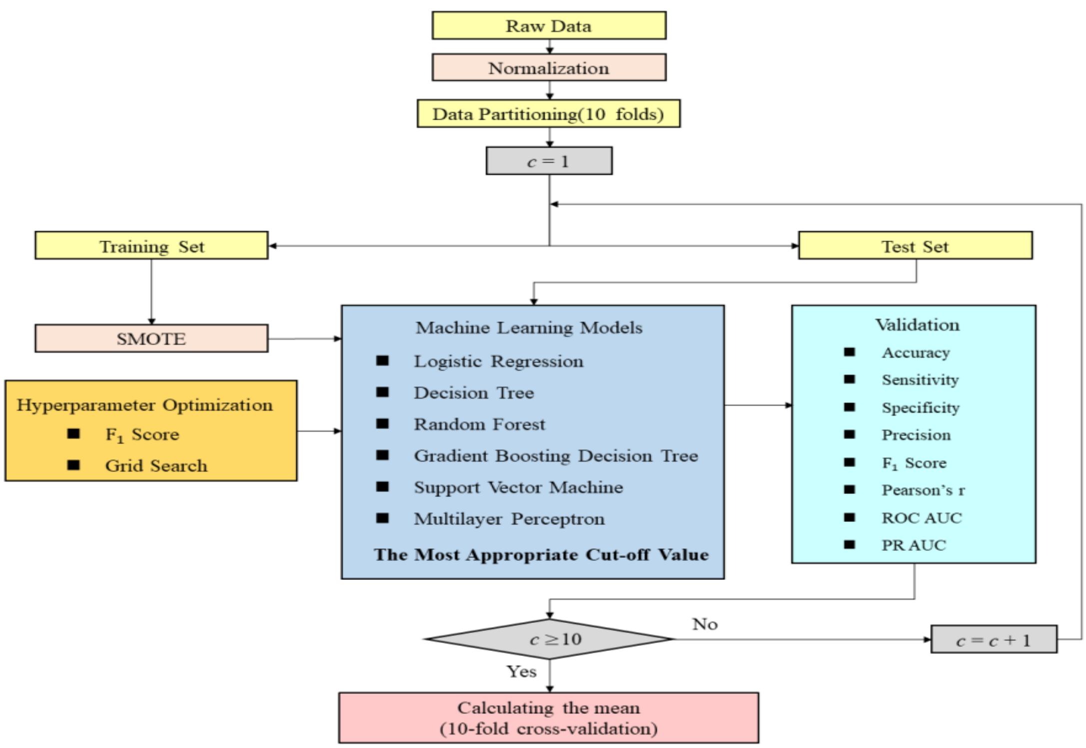


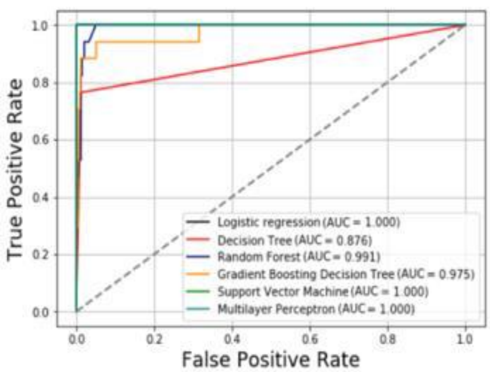
Fig.2 Flow chart of proposed method

To solve the phenomenon of different dynamic ranges for the six input variables, we apply the normalization of Min-Max scaling, to normalize input data into the interval 0~1. Min-Max normalization executes a linear transformation on the original data. Each of the actual data *d* of feature *x* is mapped to a normalized value adjusted in the range of 0 to 1. 10-fold cross validation is utilized in this paper. The data numbers illustrated by one fold are detailed. For the prediction of the presence of any suicide ideation (suicide ideation ≥ 1), the numbers for training and test sets are 3191 (class 0: 3080, class 1: 111) and 355 (class 0: 338, class 1: 17), respectively. For the prediction of more severely intense suicide ideation (suicide ideation ≥ 2), the numbers for training and test sets are 3191 (class 0: 3157, class 1: 34) and 355 (class 0: 347, class 1: 8), respectively. This imbalance in the dataset between class 0 and class 1 is obvious. This problem is addressed by applying the synthetic minority over-sampling technique (SMOTE). The training data for class 1 are pre-processed by SMOTE to 3080 and 3157 for the two predictions, respectively. Support vector machine (SVM) with linear kernel (Linear SVM) is used for our proposed method. A data point is viewed as a 6-dimensional vector and we separate such points with a hyperplane. This linear SVM constructs the maximum-margin hyperplane so that the distance from it to the nearest training data point of any class (class 0 or class 1) is maximized. If the training set is not linearly separable, soft-margin SVM allows the fat decision margin and some outliers are inside or on the wrong side of the margin. Our method adopts soft-margin SVM, which minimizes training error traded off against margin. Regularization strategy with a constraint by regularization term aims to fit training set data and avoid over-fitting. $\ell 2$-norm is utilized in SVM for our method. The regularization hyperparameter is optimized in our algorithm to control overfitting.

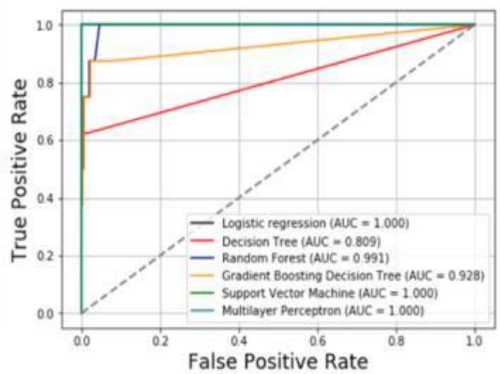
Random forest (RF), an ensemble machine learning technique, constructs multiple decision trees and collects them together for classification. The training algorithm adopted in our method for random forest is the bootstrap aggregating (bagging) technique. RF builds multiple CART models with different samples and different initial variables. In each decision tree, a random subset of the features is taken into consideration for splitting a node. The individual trees are not correlated with each other and thus the trees in random forest of our method are not pruned. The final prediction result is according to the majority-votes model from the multiple DTs. RF combines the merits of feature selection and bagging. The decision tree number is the hyperparameter to be optimized. Gradient boosting decision tree (GBDT) is also an ensemble machine learning method and constructs multiple additive decision tree models. The DTs fitting the gradient on pseudo residuals of previous cumulative models are repeatedly trained to minimize mean squared error. This sequential stepwise manner combines the performance of weak learners (i.e., DT here) in an iterative fashion into a single strong learner to increase the accuracy of prediction. Our algorithm uses the maximum tree depth as the hyperparameter to be optimized to avoid over-fitting. Multilayer perceptron (MLP) consists of an input layer, hidden layers and an output layer for our algorithm. In fully connected MLP, each node in one layer connects with a certain weight to every node in the following layer. In the forward propagation, the signal flow moves from the input layer through the hidden layers to the output layer. Learning is carried out through backward propagation. The loss function consists of cross entropy and $\ell 2$-norm regularization to prevent over-fitting. The optimizer Adam is adopted in our method. Besides regularization hyperparameter, the numbers of hidden layers, neurons and iterations are also used as the hyperparameters to be optimized in our MLP method.

IV. RESULTS AND DISCUSSION

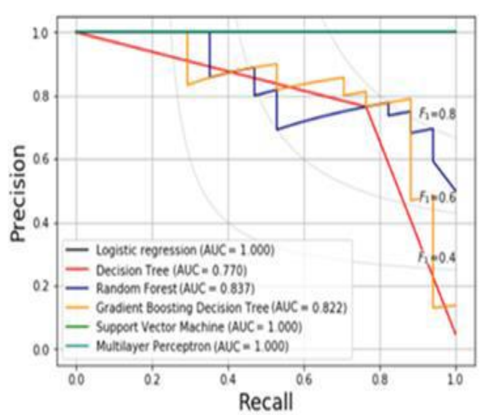
The performance comparisons of each machine learning technique with the BSRS-5 score ≥7 [9] assessed by accuracy, sensitivity, specificity, precision, F1 score, r value, are under curve(AUC) of ROC curve and the AUC of PR curve are shown as the average of the 10-fold cross validation. The p values for all techniques are <0.0001. The accuracies for all of the six machine learning methods are over 98%. The results show that the MLP and SVM provide the best predictions. The second is the LR, and then the three tree-based methods. The RF and GBDT yield overall better results than that of the DT. The prediction results for suicide ideation ≥ 1 are better than those of suicide ideation ≥ 2. The ROC curves and the PR curves and the corresponding AUCs are shown in Fig. 3, for one of the 10-fold cross validation. The areas under ROC and PR curves reach to 1 for MLP and SVM. The tendency is similar with the results. The learning curves for the six proposed methods for suicide ideation ≥ 1 are shown in Fig. 4. The learning curves depict an improvement in F1 score when there are changes in the number of iteration (logistic regression, support vector machine and multilayer perceptron) or tree depth (decision tree, random forest, gradient boosting regression tree). All curves for the six proposed methods exhibit convergence well. The distributions of variable importance for six input parameters except MLP are shown in Fig. 5. The average values of feature importance of the 10-fold cross validation ar also shown. All of the five machine learning techniques take the BSRS-5 score as the most important variable and the proportion is even larger for the case of suicide ideation ≥ 2. For both of DT and GBDT, the anxiety dimension has less importance compared to other three methods. For the screening instrument to predict suicide ideation proposed in [8], the sensitivities for psychiatric group, community group and general medical group are 83.76%, 21.57%, and 10.57%, respectively, and the specificities for the three groups are 72.17%, 99.49%, and 99.88%, respectively. As compared with the BSRS-5 score ≥7 in [9], a conventional criterion, for the presence of suicide ideation ≥ 1, the proposed algorithms can improve the performances of accuracy, sensitivity, specificity, precision, the AUC of ROC curve and the AUC of PR curve up to 5.7%, 35.9%, 4.6%, 65.2%, 4.3% and 53.2%, respectively; and for the presence of more severely intense suicide ideation ≥ 2, the improvements are 6.1%, 26.2%, 5.8%, 83.5%, 2.8% and 64.7%, respectively. Instead of only considering the BSRS-5 score in screen of suicide ideation like [8] and [9], our algorithm additionally takes the five psychopathological domains which are related to the BSRS-5 score, i.e., anxiety, depression, hostility, interpersonal sensitivity and insomnia as the input variables, and our schemes incorporating machine learning techniques provide better results than those of [8] and [9]. In addition, we add several critical physiological data including age, sex, body height, body weight, waist circumference, heart rate, systolic blood pressure, diastolic blood pressure and physical activity on the initial inputs of the BSRS-5 score and related five psychopathological domains in our proposed models. We find that the performances are only improved by incorporating these nine physiological data into the model of logistic regression. All of the performances of logistic regression regarding accuracy, sensitivity, specificity and precision reach 100% for suicide ideation ≥ 1 and 99.9% for suicide ideation ≥ 2. However, for the other five machine learning methods, the performances are not getting better with additional inputs of these physiological data. As the incidence of suicide attempts is relatively low, a meta-analysis reveals that the utility of suicide ideation for predicting later suicide is limited by low positive predictive value and modest sensitivity [41]. Machine learning techniques for the BSRS-score and related five psychopathological domains can be aimed for later suicide attempts in future work.



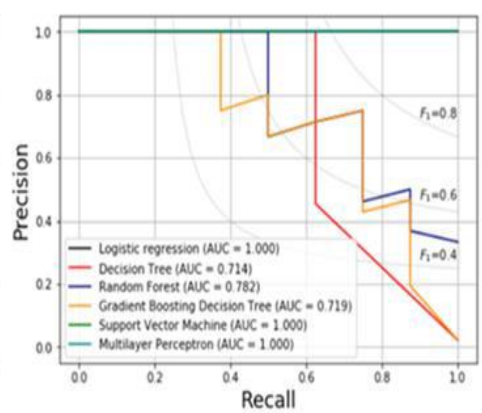
(a) Suicide Ideation ≥1



(b) Suicide Ideation ≥2

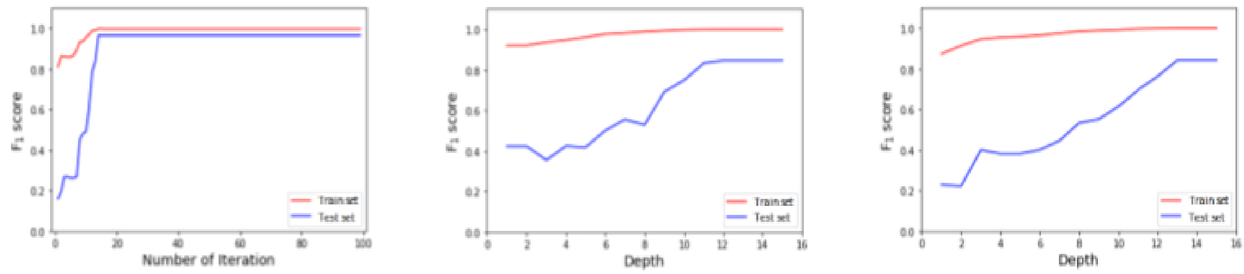


(c) Suicide Ideation ≥1

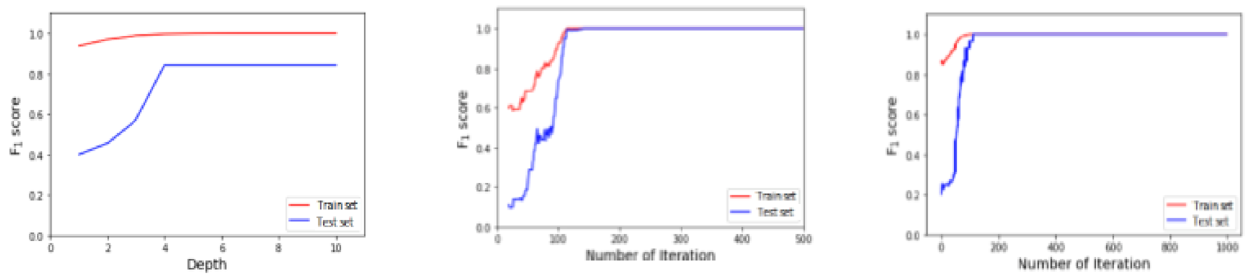


(d) Suicide Ideation ≥2

Fig.3 Receiver Operating Characteristic Curves and Precision Recall Curves



(a) Logistic Regression (b) Decision Tree (c) Random Forest



(d) Gradient Boosting Decision Tree (e) Support Vector Machine (f) Multilayer Perceptron

Fig.4 A set of learning curves for each of the six machine learning methods

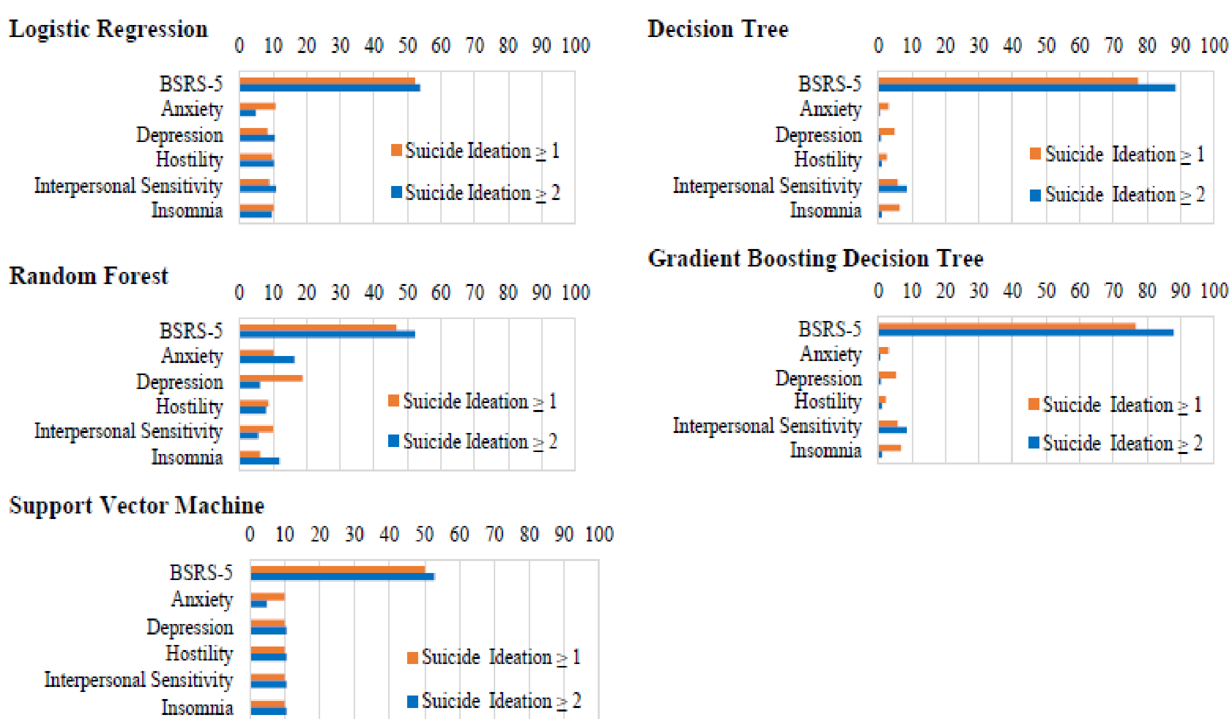


Fig.5 Feature Importance for the machine learning methods in the proposed algorithm

V. FUTURE SCOPE AND CONCLUSION

Our study uses machine learning techniques for several psychological stress dimensions training on the prediction of suicide ideation. This paper utilizes six machine learning techniques to predict the presence of any or more severely intense suicide ideation of military personnel. Normalization of input data and imbalanced classification strategy facilitate the prediction of machine learning methods. The experimental results show that the techniques of MLP and SVM provide the best performance for the two predictions. Most of the proposed machine learning techniques take the BSRS-5 score to be the most pivotal variable and the five psychopathological dimensions are also adopted as the features to improve the screening. As compared with the prior study using the BSRS-5 score only, the machine learning techniques can improve the performances of predicting suicide ideation. This work can substantially help to screen out the military personnel at high suicide risk for suicide prevention.

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