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Hybrid Ensemble Model with Optimal Weightage for Suicidal Behavior Prediction

Model Kesatuan Hibrid dengan Pemberat Optimum untuk Ramalan Tingkah Laku Bunuh Diri

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ABSTRACT

Suicidal behavior is a complex phenomenon that is contextually dependent and changes rapidly from one day to another. The problem in predicting suicidal behavior is identifying individuals and at-risk groups in crisis and at risk for suicide. The current predictive model, which uses machine learning techniques, has been shown to lack accuracy, and no study has attempted to use a voting ensemble model to predict suicidal behavior. The soft voting ensemble model demonstrated good performance in the healthcare setting, but assigning optimal weights for machine learning models is challenging. Therefore, this paper aims to propose a hybrid voting ensemble model to achieve optimal weights in predicting an individual with suicidal behavior. The results show that the proposed hybrid voting ensemble model can effectively classify an individual with suicidal behavior with an accuracy of 0.84 compared to other machine learning models (logistic regression, support vector machine, random forest, gradient boosting). Hybridization of soft voting with brute force algorithm has shown that the proposed hybrid ensemble model can find the optimal weights for the machine learning model in the context of predicting suicidal behavior. Furthermore, the proposed hybrid ensemble model shows that clinical data can be used to improve the performance of machine learning models in predicting an individual with suicidal behavior.

Keywords**:** Ensemble learning model, optimal weightage, soft voting method, suicidal behavior prediction

ABSTRAK

Perilaku bunuh diri adalah fenomena yang kompleks yang bergantung pada konteks dan berubah dengan cepat dari satu hari ke hari lain. Masalah dalam meramalkan perilaku bunuh diri adalah mengenal pasti individu dan kumpulan berisiko dalam krisis dan berisiko bunuh diri. Model meramal semasa, yang menggunakan teknik pembelajaran mesin, telah terbukti kurang tepat, dan tiada kajian yang cuba menggunakan model kesatuan undian untuk meramalkan perilaku bunuh diri. Model kesatuan undian lembut menunjukkan prestasi yang baik dalam konteks penjagaan kesihatan, tetapi memberikan berat optimum untuk model pembelajaran mesin adalah cabaran. Oleh itu, kertas ini bertujuan untuk mencadangkan model kesatuan undian hibrid untuk mencapai berat optimum dalam meramalkan individu dengan perilaku bunuh diri. Keputusan menunjukkan bahawa model kesatuan undian hibrid yang dicadangkan dapat mengklasifikasi individu dengan perilaku bunuh diri dengan ketepatan 0.84 berbanding model pembelajaran mesin lain (regresi logistik, mesin vektor sokongan, hutan rawak, penggalakan cerun). Hibridisasi undian lembut dengan algoritma *'brute force'* telah menunjukkan bahawa model kesatuan hibrid yang dicadangkan dapat mencari berat optimum untuk model pembelajaran mesin dalam konteks meramalkan perilaku bunuh diri. Selanjutnya, model kesatuan hibrid yang dicadangkan menunjukkan bahawa data klinikal boleh digunakan untuk meningkatkan prestasi model pembelajaran mesin dalam meramalkan individu dengan perilaku bunuh diri.

Kata Kunci: Model pembelajaran kesatuan, berat optimum, kaedah undian lembut, ramalan tingkah laku bunuh diri

INTRODUCTION

Suicide is one of the leading causes of death worldwide. Priority for suicide research and prevention is needed for world health services. According to the World Health Organization (2014), nearly 800,000 people are estimated to die by suicide, and suicide rates are increasing yearly. Reports on the Health for World's Adolescence indicate that suicide is the second leading cause of death among young people aged 10 to 24, and 76% of global suicides are committed in low-and middle-income countries (Ahmed et al. 2017; Turecki et al. 2019).

In Malaysia, suicidal behavior is a growing problem as the suicide rate increases yearly. Malaysia has a moderately high suicide rate of about 12 deaths per 100,000 population compared to other Asian countries (Sinniah et al. 2014). According to the National Institute of Health of Malaysia, three out of ten adults aged 16 and above suffer from mental health problems, leading to an increase in the suicide rate. The National Health Morbidity Survey 2017 showed that suicidal behavior among Malaysian adolescents has recently increased (Institute for Public Health 2018). It poses challenges for mental health providers and clinicians and raises the question of improving the early detection of suicide and prevention.

Suicidal behavior is a complex phenomenon that is contextually dependent and changes rapidly from one day to another. The problem in predicting suicidal behavior is identifying individuals and at-risk groups who are in crisis and at risk of suicide to alert them, which helps inform and support emergency responders (Boudreaux et al. 2021; Fonseka et al. 2019). Chan et al. (2011) highlighted that accurately identifying those at the highest risk for suicidal acts is one of the most essential processes for preventing suicidal behavior. Therefore, strategies to accurately predict which individuals will engage in suicidal behavior or die from it remain inadequate. However, the existing literature identifies common risk factors such as a family history of suicide attempts, child abuse, and severity of mental illness (Belsher et al. 2019).

Currently, strategies for predicting suicidal behavior are based on classification problems that require the development of robust models for classifying and predicting suicidal behavior for accurate decision-making. The use of machine learning techniques to predict suicidal behavior offers new opportunities to significantly improve risk prediction and expand the framework for suicide detection and prevention (Burke et al. 2019; Nordin et al. 2022). Most studies have used machine learning techniques to predict suicidal behavior, such as decision tree, naïve Bayes, k-nearest neighbors, support vector machine, and logistic regression (Edgcomb et al. 2021; Kessler et al. 2017; J. Oh et al. 2017).

More recently, three widely used models for ensemble methods for predicting suicidal behavior are random forest, bagging, and gradient boosting (Burke et al. 2020; Jung et al. 2019), which are used to improve the performance of machine learning techniques. An ensemble method contains several learners called base learners. The base learners are usually generated by a base learning algorithm (decision tree, neural network) from training data (Zhou 2012). Most studies have shown that ensemble methods using random forest and gradient boosting are able to classify an individual with suicidal behavior. However, no study uses a voting ensemble model to predict suicidal behavior.

In general, voting ensemble models are known to be well suited for healthcare clinical datasets due to the voting method that uses weighting in averaging the modeling probabilities, resulting in better results of prediction (Mienye et al. 2020; Saxena et al. 2021). However, in most studies, weights are assigned manually, equally, and with high model accuracy (Ali et al. 2021; Zhang et al. 2014). Thus, it is difficult to find and achieve optimal weights to improve the performance of voting ensemble models in clinical datasets. Therefore, this paper aims to propose a hybrid voting ensemble model to achieve optimal weights in predicting an individual with suicidal behaviors.

The paper is organized as follows: Section 2 presents related work on suicidal behavior prediction models with current approaches of voting ensemble models. Section 3 discusses the methodology of the proposed hybrid ensemble model for suicidal behavior prediction, Section 4 presents the results of the proposed hybrid ensemble model, and finally, Section 5 summarizes the conclusion with future developments.

RELATED WORKS

Machine learning techniques help classify many patients into general risk categories and identify potentially at-risk patients whose suicidality might otherwise have gone undetected (Fonseka et al. 2019). Models developed using machine learning techniques can model complex relationships between features and outcomes. The benefits of machine learning techniques can potentially improve the prediction of suicidal behavior, thereby improving suicide prevention and intervention efforts (Boudreaux et al. 2021).

A recent study by Oh et al. (2020) used the Bayesian network to predict suicidal ideation in the Korean population and found that the Bayesian network performed better compared to conventional logistic regression. The study by Edgcomb et al. (2021) proposed a classification and regression tree (CART) for predicting suicidal behavior and self-injury in adults with severe mental illness. The results showed that CART could predict the risk of suicide attempts with good performance (accuracy – 0.80, AUC = 0.86, sensitivity = 0.79, specificity = 0.81).

Besides that, an ensemble model has been developed for suicide prediction based on bagging, boosting and random forest. Most studies currently utilize Random Forest as a machine-learning technique for predicting suicidal behavior (Nordin et al. 2022). The study by Navarro et al. (2021) proposed a suicide attempt model for the young population using Random Forest, while Cho et al. (2021) proposed the same technique for suicide deaths among the elderly population. Both studies highlighted the good performance of both Random Forest models for specificity (0.76 – 0.833) and AUC (0.76 – 0.818).

Although the ensemble model can classify an individual with suicidal behavior and achieve moderate performance, no study has applied a voting method to predict suicidal behavior. The voting method is the simplest way to combine base learners to produce a final prediction based on a majority vote (hard voting) or the average sum of predicted probabilities (soft voting) in the class label (Alpaydin 2010). In the simplest case, all base learners are weighted equally, and simple voting is equivalent to averaging. Simple majority voting is a rule that selects one of many alternatives based on the predicted classes with the most votes (Zhou 2012). Personalized weights are also assigned to the specific classes in the base learners that have a higher importance in the classification and prediction process.

Mahabub (2019) proposed a voting method using a hard scheme where the three best machine learning models (multiple layer perceptron, support vector machine, k-nearest neighbors) were chosen and used to determine the majority votes of each classifier in predicting diabetes. The study shows that the voting method provides better accuracy compared to other individual machine learning models. In the study by Sherazi et al. (2021), a soft voting classifier was used to predict and diagnose major adverse cardiovascular events (MACE) in patients with the acute coronary syndrome. Three machine learning models (random forest, extra tree, gradient boosting machine) are used to develop a soft voting classifier and aggregate the performance of the models. The study shows that the soft voting classifier performs significantly better than the three individual models. However, the weights used for the soft voting ensemble classifier are adjusted and manually selected for predicting patients based on the average of probabilities between the three classifiers used.

Devi (2017) proposed an extended weighted voting ensemble method for breast cancer detection. The ensemble models of machine learning (k-nearest neighbors, naïve Bayes, and support vector machines) are used for breast cancer classification. The weights for each classifier are manually assigned as 50, 30, and 20, respectively. They extend the threshold weightage to 70, and the decision depends on the mandatory condition assigned to each classifier, where malignant cases are considered true if the value is above 70. Although the results show that the proposed method achieves better performance, the weighting was assigned based on the accuracy of the performance model and the probability of each sample in the class being used.

Also, in the study of Osamor and Okezie (2021), a combination of naïve Bayes and support vector machine was proposed for ensemble learning (voting) in predictive tuberculosis diagnosis. The weighted voting ensemble method was improved based on the classifier’s performance accuracy based on the training set. They assigned a weight to each classifier based on the accuracy of the classifier divided by the sum of the accuracy of all classifiers used. The classification result that received the most votes and high accuracy is the final result for the predictive ensemble model.

In the study by Saxena et al. (2021), the researchers used a majority voting classifier to predict syncope. Syncope is a situation in which people accidentally fall due to sudden abnormal changes in their health parameters, such as blood pressure, heart rate, and sugar levels. For predicting syncope, six machine learning models are used as the base learner for voting ensemble learning: logistic regression, decision tree, random forest, K-nearest neighbors, support vector machine, and naïve Bayes. They assign the same weights to each machine learning model because each model is important for the syncope prediction. All models are assigned the same weight, which is 1. The proposed model increases model accuracy and performance due to multiple support of the base learners and decreases the probability of overfitting the model.

An ensemble is an effective technique that combines different machine-learning models to improve overall prediction accuracy. Soft-voting ensemble methods are effective and efficient in classification problems compared to hard-voting ensemble techniques (Ali et al. 2021). The advantage of soft voting is that it uses averaging of probabilities, which leads to better results and performance. Soft voting covers the weaknesses of the individual base classifiers and outperforms the overall results by aggregating multiple predictive models. Soft voting is also known as weighted voting, where the voting weights should vary between the different output classes in each classifier. The weights should be high for the output class in which the classifier performs well. However, manually assigning weights for soft voting ensemble learning based on different base learners is difficult and challenging (Zhou 2012). Therefore, choosing the suitable and optimal voting weights for all classifiers is important.

In addition, equal weighting was applied in most studies, and the classifiers with high accuracy were weighted more heavily (more weight) compared to other classifiers. Therefore, no study tries to find the optimal weighting for the clinical dataset. For different applications, such as healthcare, the ensemble learning techniques need to be modified to suit the structure of the specific problem, including the prediction of suicidal behavior. Therefore, the main contribution of this study is to propose a hybrid ensemble model to achieve optimal weighting in predicting an individual with suicidal behaviors.

METHODOLOGY

Figure 1 presents the overview of the proposed hybrid ensemble model for the predictive model for suicidal behavior, which uses the hybrid voting method to determine the optimal weighting of each machine learning model.

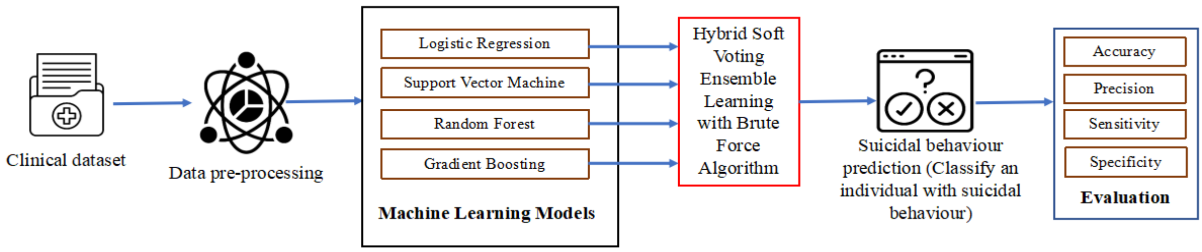

FIGURE 1. Overview of hybrid ensemble model for suicidal behaviour prediction

Clinical Dataset and Data Pre-Processing

The clinical research dataset is used to evaluate the proposed hybrid ensemble model for suicidal behavior prediction. This dataset focuses on a specific group of psychiatric inpatients in Malaysia and includes 75 individuals aged 18 to 76 years, consisting of 33 males and 42 females who have been treated for depressive disorder (Chan et al. 2011). The outcome of the dataset is a binary classification task where an individual is classified into suicide attempts and non-suicide attempts. There are thirteen features available in the clinical dataset: age, religion, ethnicity, history of suicide attempt, suicide ideation, depression severity, comorbid medical condition, psychotic features, alcohol abuse, sexual abuse, any substance abuse, and substance dependence and suicide attempt. All of the features are used to train the predictive model.

Data pre-processing is essential in predictive models to classify an individual with suicidal behaviors. Two main tasks were applied to the clinical dataset: data encoding and data scaling. The categorical features such as religion, ethnicity, suicide ideation, history of suicide attempt, and depression severity are coded to convert them into numerical values to be easily fitted into the machine learning models. After data encoding is completed, the various features are in their respective measurement ranges, which can dilute the effectiveness of the model development. Therefore, the data scaling is performed using the standardization technique to scale the features. It assigns the values representing the difference between the standard deviations and the mean. StandardScaler is used to scale the values to improve the performance of machine learning classifiers and increase the stability with a standard deviation and a mean value. There are no missing values in this clinical dataset, therefore, no imputation of the missing values is performed.

Hybrid Ensemble Learning Model

Four machine learning techniques, namely logistic regression, support vector machine, random forest, and gradient boosting, were used to solve suicidal behavior problems in classifying an individual with suicidal behaviors. These four machine-learning techniques have been widely accepted to classify individuals into suicide attempters and non-suicide attempters (Burke et al. 2019). Each of these techniques has been used as a state-of-the-art machine learning technique due to its ease of implementation and robustness (Boudreaux 2021). Therefore, the four machine learning techniques are used as a baseline for the ensemble learning model.

The hybrid ensemble learning technique is proposed to improve the accuracy of the predictive model using optimal weighting and overcome the problem of limited sample size in predicting suicidal behavior. Ensemble learning combines different classifiers to improve the predictive power and stability of the classification model (Raza 2019). Initially, all the base classifiers are trained, and each classifier gives an individual decision. These individual decisions are combined based on the probability values that indicate the predicted value for a particular class. Therefore, combining several single prediction models using a soft-voting ensemble model is proposed.

In the soft voting ensemble model, the predictions are weighted based on the importance of the classifier and merged to obtain the sum of the weighted probabilities. The target label with the largest sum of weighted probabilities is selected because it has the largest voting value. In most studies, weights are assigned manually per classifier, equally weighted and based on the higher accuracy of base learners (Sherazi et al. 2021). Thus, it is difficult to find the optimal weightage for each classifier of the model.

This paper attempts to hybrid ensemble model for suicidal behavior prediction to solve the problem of assigning weights for the voting method using the brute force algorithm. When an ensemble of classifiers is constructed, the proposed hybrid soft-voting classifier assigns unique voting weights to each classifier. The brute force algorithm is integrated into the voting classifiers to determine the problem of finding the optimal weights for each classifier. A brute force algorithm is an approach that finds all possible solutions to find a satisfactory solution to a given problem. In the context of ensemble learning, the brute force algorithm finds a solution for optimal weights by iteratively considering all possible solutions for the weights one by one, shown in Figure 2. The advantage of the brute force algorithm is that this algorithm is well suited to solving search problems and finding the maximum weights in a list of multiple classifiers.

```
Algorithm 1: The proposed hybrid ensemble model
Input: Clinical data using patient information.
Output: Prediction of suicidal behaviour in an individual.
Voting scheme = 'soft'
Procedure assign_optimal_weight
for w1 in range (1,4):
   for w2 in range (1,4):
      for w3 in range (1,4):
         for w4 in range (1,4):
            if len (set((w1,w2,w3,w4))) == 1:
            continue until all weights are equal to 1.
Return weight combination of outputs of classifiers
C1 = logistic_regression()
C2 = support_vector_classifier()
C3 = random_forest_classifier()
C4 = gradient_boosting_classifier()
Procedure ensemble_model(X, y)
   Soft_voting_classifier = concatenate(classifier=[c1,c2,c3,c4], weights=[w1,w2,w3,w4])
   Soft_voting_classifier.fit(X, y)
   Predictions= soft_voting_classifier.predict()
Return the prediction of the suicidal behaviour in an individual.
```

FIGURE 2. The algorithm proposed hybrid ensemble model

The parameters settings of each classifier are performed using GridSearchCV, a search function in the Scikit-Learn library. The optimal parameters for each classifier is stated as follows:

1. logistic regression (solver: liblinear, C: 1.0);
2. support vector machine (C: 1.0, kernel: linear, gamma: 0.01, probability: true);
3. random forest (criterion: gini, maximum depth: 3, number of estimators: 40);
4. gradient boosting (loss: deviance, learning rate: 0.01, maximum depth: 3, number of estimators: 150).

The parameters for the hybrid ensemble model are estimators (logistic regression, support vector machine, random forest, gradient boosting), and voting scheme is soft. The weight optimization for hybrid ensemble model using the brute force algorithm is logistic regression (1.0), support vector machine (1.0), random forest (2.0), and gradient booting (2.0).

Evaluation of Hybrid Ensemble Model

The performance of the hybrid ensemble model for binary-class settings is evaluated using accuracy, precision, sensitivity (recall), and specificity based on the suggestion taken from the study by Sokolova & Lapalme (2009). Classification accuracy is the ratio of correct predictions to the total number of predictions, generally known as how often the classifier is accurate. The result where the model correctly predicts the positive class is known as true positive, t_p, while the result where the model correctly predicts the negative class is known as true negative, t_n. Moreover, false positive, f_p is the result where the model incorrectly predicts the positive class and false negative, f_n is the outcome where the model incorrectly predicts the negative class.

The accuracy measure for these predictive models is illustrated in (1).

$$Accuracy = \frac{(t_p + t_n)}{(t_p + f_n + f_p + t_n)} \quad (1)$$

The precision is used to quantify the number of positive class predictions that belong to the positive class (2).

$$Precision = \frac{t_p}{t_p + f_p} \quad (2)$$

The sensitivity is known as recall, or true positive rate, is the proportion of people who test positive among all those who are attempting suicide (3).

$$Sensitivity = \frac{t_p}{t_p + f_n} \quad (3)$$

The specificity of a test is the proportion of individuals who are negative among all those who do not attempt suicide (4).

$$Specificity = \frac{t_n}{t_n + f_p} \quad (4)$$

Stratified five-fold cross-validation was used to evaluate the models. Generally, 5-fold cross-validation divides the data into five foldings (equal-sized parts). The model has then trained with k (5) -1 folds, which are combined into a training set, and the last fold is used as the test set. The process is repeated k times using a different fold as the test set. The performance of the models for each of the five iterations is then averaged to obtain an overall score (Nordin et al. 2021).

RESULT AND DISCUSSION

In this section, the results of the proposed hybrid ensemble model for predicting suicidal behavior are discussed. The experiment compared the performance of all machine learning models (logistic regression, support vector machine, random forest, gradient boosting, hybrid soft voting) using the clinical dataset of patients with depressive disorders. Table 1 shows the evaluation of the proposed hybrid ensemble models.

TABLE 1. Evaluation of the proposed hybrid predictive models

Machine learning models	Accuracy	Precision	Sensitivity	Specificity
Logistic regression	0.77	0.81	0.76	0.62
Support vector machine	0.78	0.80	0.77	0.63
Random forest	0.79	0.81	0.79	0.69
Gradient boosting	0.83	0.82	0.83	0.75
Hybrid soft voting	**0.84**	**0.83**	**0.84**	**0.76**

Overall, the proposed hybrid soft voting achieved the highest classification accuracy of 0.84, followed by gradient boosting (0.83), random forest (0.79), support vector machine (0.78), and logistic regression (0.77). For the precision value, all machine learning models achieved a high precision of above 0.80, with the proposed hybrid soft voting achieving the best value of 0.83. In addition, the proposed hybrid soft voting achieved high sensitivity (0.84) and high specificity (0.76).

Based on Table 1, it can be shown that the hybrid ensemble model using soft voting method able to classify an individual with suicidal behaviors with high accuracy and high precision compared to other machine learning models. The optimal weightage method using the brute force algorithm can find the optimal weightage among machine learning models and can achieve the best performance.

Because the clinical dataset on individuals with suicidal behavior is difficult to obtain and confidential, this paper was not compared with existing work due to differences in sample size and features available in the datasets. Although this paper was not compared to existing work, the overall results of the predictive models are consistent with existing work on predicting suicidal behavior. This is evidenced by several studies using the random forest as a machine learning model (Jung et al. 2019; Ribeiro et al. 2019; Walsh et al. 2017) to predict suicidal behavior and achieved an average accuracy of 0.80 to 0.85. Thus, the proposed hybrid ensemble model for suicidal behavior is able to increase the performance of the predictive models.

CONCLUSION

In conclusion, the hybrid ensemble model is proposed for the suicidal behavior predictive model to find the optimal soft-voting weighting. The ensemble learning technique uses a soft voting method with the integration of a brute force algorithm to find optimal weights for each machine learning technique. The optimal weights of each predictive technique (logistic regression, support vector machine, random forest, gradient boosting) are used to predict an individual with suicidal behavior and improve the classification performance of the predictive models. The proposed hybrid soft voting outperformed the other machine learning techniques with an accuracy of 0.82 to 0.84. The proposed hybrid ensemble model was also shown to be able to discriminate patients with suicidal behavior based on clinical and socio-demographic features. It also shows that the good implementation of ensemble learning techniques can be used to predict suicidal behavior in the future.

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