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An Investigation of Suicidal Ideation from Social Media Using Machine Learning Approach

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Abstract

Despite improvements in the detection and treatment of severe mental disorders, suicide remains a significant public health concern. Suicide prevention and control initiatives can benefit greatly from a thorough comprehension and foreseeability of suicide patterns. Understanding suicide patterns, especially through social media data analysis, can help in suicide prevention and control efforts. The objective of this study is to evaluate predictors of suicidal behavior in humans using machine learning. It is crucial to create a machine learning model for detection of suicide thoughts by monitoring a user's social media posts to identify warning signs of mental health issues. Through the analysis of social media posts, our research intends to develop a machine learning model for identifying suicide ideation and probable mental health problems. This study will help immensely to comprehend the environmental risk factors that influence suicidal thoughts and conduct across time. In this research the use of machine learning on social media data is an exciting new direction for understanding the environmental risk factors that impact an individual's susceptibility to suicide ideation and conduct over time. The machine learning algorithms showed high accuracy, precision, recall, and F1-score in detecting suicide patterns on social media data whereas SVM has the highest performance with an accuracy of 0.886.

Keywords: Behavior, Ideation, Machine Learning, Prediction, Social Media, Suicide.

Introduction

Conforming to the World Health Organization, each year more than 800,000,000 individuals commit suicide[1-3]. The WHO reports that suicide is the second greatest cause of mortality among 15–30-year-olds globally[4-5]. The suicide rate is high everywhere in the globe, not only in nations with the highest GDPs. About 77% of the world's suicides occurred in countries with low or moderate per capita income. Since its inception in 1948, suicide prevention has been one of the top priorities of WHO and they released its first global suicide prevention strategy in 1952. This plan puts an emphasis on training and development for professionals, creating and implementing policies, mobilizing communities, educating and doing research. A wide range of emotions, but not limited to shock, wrath, guilt, sorrow, and worry, may contribute to suicidal thoughts, which is a severe issue affecting individuals of all ages. It can refer to the act of seriously considering, or even acting on, one's intent to commit suicide.

In India more than 100000 individuals commit suicide each year. Professional career troubles, loneliness, abuse, violence, family issues, mental disorders, alcoholism, financial loss, chronic pain, and many more circumstances might lead to suicide. The National Crime Records Bureau[6] (NCRB) of India released data in 2022 showing that there were approx 1,64,033 suicides reported in India in 2021. This was a 7.2% increase from the number of suicides reported in 2020. The NCRB also reported that the suicide rate in India was 12 per lakh population in 2021, which is a 6.2% increase from the suicide rate in 2020.

Studies evaluating emergency room evaluations of suicidality have shown that adolescents are more likely to disclose suicidal ideation using electronic means, such as online forums, blogs, instant messengers, text messages, and emails. There is a correlation between online manifestations of suicidal ideation and psychometrically assessed suicide risk, however it is unclear whether these online expressions are similar to the suicidal danger triggered by doctors. Online suicidal thoughts are associated with psychometrically rated suicide risk, although it is unclear how much they reflect clinician-triggered suicide risk. Nearly[7] one-third (34.5%) of all suicide victims were between the ages of 18 and 30, and nearly one-third (31.7%) were between the ages of 30 and 45. Many of the attendees were students. There were as many as 13,039 student suicides. It has been repeatedly shown that the highest suicide rate occurs among the country's young, productive individuals; as a result, the federal and state governments need to tackle this problem seriously.

Depression may lead to suicide if left untreated for too long, even though most people with suicidal[8-9] thoughts do not act on them. Professionals in mental health and pharmaceuticals may be able to help with suicidal thoughts. With the help of medical specialists and prescription drugs, suicidal thoughts can be controlled. Many individuals now use the internet to talk about their suicide ideas with others. Recognizing and responding to mental health issues early on may greatly reduce the likelihood of suicidal thoughts or behavior.

The objective of machine learning[10] is for a computer to be able to learn and develop on its own, depending on what it has seen in the past, without being explicitly instructed. Identifying a specific pattern or piece of information might be difficult, even after thoroughly exploring the material. These conditions call for the application of machine learning in order to decipher the underlying pattern and data. Machine learning advocates for the idea that a machine, with enough training and appropriate data, can learn to answer both general mathematical problems and more specific ones. New possibilities for significantly improving risk prediction and enhancing suicide prevention frameworks are made possible by the use of artificial intelligence and machine learning. Despite the promising findings, assessing, disseminating, and influencing the field of AI and ML research into suicide prevention is challenging since it involves so many different medical and computer science fields[11].

The most significant contributions of this study are outlined in the list below:

- Analyzing the suicidal and non-suicidal texts to determine the most frequent words by applying the appropriate word embedding and other data wrangling techniques.
- The proposal investigates the suicidal patterns in different states in India and the major causes of suicides.
- The purpose is to identify suicidal patterns and tendencies, by proposing a machine learning model which uses the data and predicts suicidal vulnerabilities.
- To evaluate how well the suggested machine learning model performs compared to other models, by analyzing various performance metrices.

The rest of the paper is outlined as follows. A comprehensive literature survey has been pursued in next section. Then authors have presented the methodology of the proposed system. The result analysis along with discussion is presented and followed by conclusion is offered in final section.

Literature Survey:

To improve the accuracy of predictions produced with large datasets, machine learning methods enable computers to create complex classifiers as a kind of artificial intelligence. Due to the limitations of conventional research methods, including high costs and clinical obstacles, the likelihood of bias, and limited generalizability, researchers have begun to

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use large data in conjunction with sophisticated predictive modeling tools.

The authors[12] created and tested a suicide ideation detection system that uses ML and hybrid DL methods to analyze the mental health of social media users. The proposed technology can detect suicidal intent in users' posts to identify those who need medical attention and minimize suicide rates. A study by Brown[13] et al. is one of the studies to actively utilize data from an SN platform to acute SI prognostic effectiveness. Logistic regression was used to model acute SI in German teens with a lifetime history of SI. The researchers did not investigate their model's out-of-sample predictive power, prohibiting them from examining model generalization and evaluating their results' broader relevance.

In extensive literature analysis[14], authors asserted that young people often report suicide risk factors to their online networks, such as Facebook and Twitter, but rarely to their doctors. The authors note that emergency rooms' social media analysis tools may improve clinical judgement. Tweeting[15] about suicide ideas was strongly related with self-reports of suicidal thoughts and conduct in a cross-sectional study of 1000 Twitter users in their 20s, suggesting that Twitter outcome measures may be good predictors of genuine suicide. Research[16] shows that schizophrenia is associated with an increased likelihood of tweeting about suicidal thoughts and behaviors.

Twitter also lets people form suicide agreements and find suicide partners[17]. Major health and disease items are more likely to be retweeted by major media outlet followers, whereas mental health articles are more likely to be retweeted[18]. Around 30% of tweets sent by major media outlets on mental health suggested suicide[19]. A recent systematic evaluation of publications in the use of technology for suicide prevention was conducted[20]. Just 13.1% of the articles looked at focused on artificial intelligence, while 12.9% focused on social networks. Despite technology promises of remedies to address and prevent suicide, the authors discovered that much untapped potential remains in applying cutting-edge technical innovations to anticipate suicide risk. By examining the tweets of 135 study participants, the authors of[21] confirmed the efficacy of a machine learning strategy using the LIWC approach in making suicide prediction.

Preventing suicide attempts begins with an accurate diagnosis of suicidal intents based on the detection of consistent linguistic patterns in social media postings.

This research on German teens with a lifetime history of SI utilized LIWC[22] predictions from interview and Instagram post content and last month's Instagram activity. The current model pipeline revealed that linguistic and SN activity features may predict acute SI with 70.2% accuracy. This work has implications for suicide risk identification and prevention in the setting of online social interaction.

Suicide[23] prevention programs for transgender and gender nonconforming youth should emphasize building a community of understanding and acceptance around the young. Connected[24] to suicide young adults frequently utilize the internet, especially those who exhibit suicidal thoughts and behaviors. Internet users visited both hazardous and beneficial websites, demonstrating that there are potential dangers online as well as opportunities for suicide prevention. The authors[25] enhanced the effectiveness of a random forest classifier to better identify tweets that include suicide ideation. The purpose of this research[26] is to develop a classifier that uses text mining techniques applied to the titles and body of forum posts to distinguish between suicidal and non-suicidal discussions.

Consensus with previous non-ML research is highlighted, while newer risk variables and methods hint to sleep, circadian, and neurological substrates, as well as user data. Suicide is a major cause of death, yet it is difficult to predict since it is so uncommon in the community. The ability to provide precise medication in the prevention of suicide is a unique potential of AI and ML applications, particularly those that can handle large and complex information.

System Model and Methodology:

In this part, authors discussed the methodology of the proposed system model. This process includes procedures to eliminate potentially dangerous null or unbounded values, ensuring the system's dependability. In the end, formatting, cleaning, and sampling are everything. The cleaning process is carried out to complete any unfinished data or recover any lost data that may have occurred. If appropriate data are used for sampling, the time needed to create the algorithm may be minimized. The authors must choose an acceptable modelling technique or strategy based on the desired objectives. The method of proposed model is presented in Fig. 1.

❖ Mathematical Model:

▪ Logistic Regression:

The sigmoid function is used to predict the output in logistic regression. This function returns a probability value between 0 and 1. Usually, 0.5 is considered a threshold value for classification. For binary classification problems, if the sigmoid function returns a value greater than the threshold value, it will be considered 1, otherwise it will be considered 0. For multiclass classification problems, it divides the features into +ve & -ve

$y = \frac{1}{1+e^{-x}}$ Here, x is the input features multiplied by θ. Initially, the random value of the θ will be provided.

$$h = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3 + \ldots + \theta_n x_n$$

Here $x_1, x_2, x_3..x_n$ are input features and $\theta_1, \theta_2, \theta_3, \ldots \theta_n$ are randomly initialized values. θ_0 is a biased term. To create a relation between input and target features, the Logistic Regression model updates the θ values. The cost function determines the difference between the actual and predicted value.

$$J = -\frac{1}{m}[\sum y^i log h^i + (1 - y) log(1 - h^i)]$$

Where m is the number of training data, y is the actual target value, and h is the predicted target value. On the other hand, to update the θ values in each iteration gradient descent is used.

$$\theta = \theta - \alpha \sum (h^i - y^i) x^i_j$$

▪ SVM:

When the data is non-linearly separable, $y_n [w^T \phi(x_n) + b] \leq 0, \ \exists n$ In each iteration, a penalty will be added for misclassification. It is denoted as β. If it is able to classify correctly, the β = 0, for misclassification, penalty value, β > 1. Using c, which is a hyperparameter, is used to regularize the β.

$$min_{w,b,\{\beta n\}} \frac{1}{2} \lVert w \rVert_2 + C \sum \beta_n$$

$$y_n [w^T \Phi(x_n) + b] \geq 1 - \beta_n; \quad \beta_n \geq 0, \ \forall n$$

C = 0 denotes a less complex boundary when not penalized. On the other hand, when the c value is higher for a small slack, the model will be highly penalized. So, hyperparameter C is important to avoid the problem of overfitting and underfitting. It is the primal form. It needs to be converted into a Lagrangian form.

$$L(w,b,\{\beta_n\},\{\lambda_n\},\{\alpha_n\}) = \left[\frac{1}{2} \lVert w \rVert_2 + c \sum \beta_n\right] + \sum[\alpha_n\{1 - \beta_n - y_n \ [w^T \Phi(x) + b]\}] + \sum \alpha_n\{-\beta_n\}$$

Dual Form:

$$max_{\{ai\}} g() = \sum \alpha + \frac{1}{2} \sum \alpha_m \alpha_n y_m y_n \phi^T(x_m) \phi(x_n)$$

$$\alpha_m, \lambda_n \geq 0, \ \forall n ; \sum \alpha_n y_n = 0; C - \alpha_n - \lambda_n = 0$$

The Φ can be solved by kernelization. The kernel $k : \phi X \phi \rightarrow R$, is basically a feature map which satisfies,

$$k(x,x') = (\omega(x),\omega(x'))\psi$$

▪ Gradient Classifier:

Input: training set $\{(x_i,y_i)\}^n_{i=1}$, a differentiable loss function $L(y,F(x))$, number of iterations M.

Algorithm:

Step 1: Initializing the model with a constant value:

Step 2: For m = 1 to M:

Step 2.1: Compute pseudo-residuals: $r_{im} = -\left[\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)}\right]_{F(x) - Fm-1(x)}$ $for\ i = 1,\ldots,n$

Step 2.2 : Fit a base learner $h_m(x)$ to pseudo-residuals
Step 2.3 : Compute multiplier, γ_m
Step 2.4 : Update the model: $F_m(x) = F_{m-1}(x)$
Step 3: Output $F_M(x)$

▪ Random Forest:

A random forest is a classifier based on a random forest family of classifiers based on a family of classifier $h(x \mid \theta_1), \ldots, h(x \mid \theta_k)$ based on a classification tree with parameters θ_k randomly chosen from model random vector Θ. For the final classification (which combines the classifiers $\{h_k(x)\}$), each tree casts a vote for the most popular class at input x, and the class with the x most votes wins. Specifically given data D = $\{(X_i,y_i)\}^n{}_{i\,=\,1}$: Authors train a family of classifiers $h_k(X)$. Each classifier $h_k(x) \equiv h(x|\theta)$ is in our case a predictor of n. $y = \pm 1$ = outcome associated with input x.

- **KNN:**

Step 1: Selecting the number k of the neighbors.
Step 2: Calculate the Euclidean distance of the k neighbors of neighbors.
Step 3: Take the k nearest neighbors as per the Euclidean distance.
Step 4: Among the k neighbors, count the no. of data points in each category.
Step 5: Assign the new data points to that category for which the number of neighbors is maximum.
Step 6: Model is ready.

- **Gaussian NB:**

Gaussian NB is based on the Bayes' theorem. p(A | B) = $\frac{p(B\mid A)\,.p(A)}{p(B)}$, Where, p(A | B) = posterior probability, p(B | A) = Likelihood probability, p(A) = prior probability, p(B) = Marginal Probability.

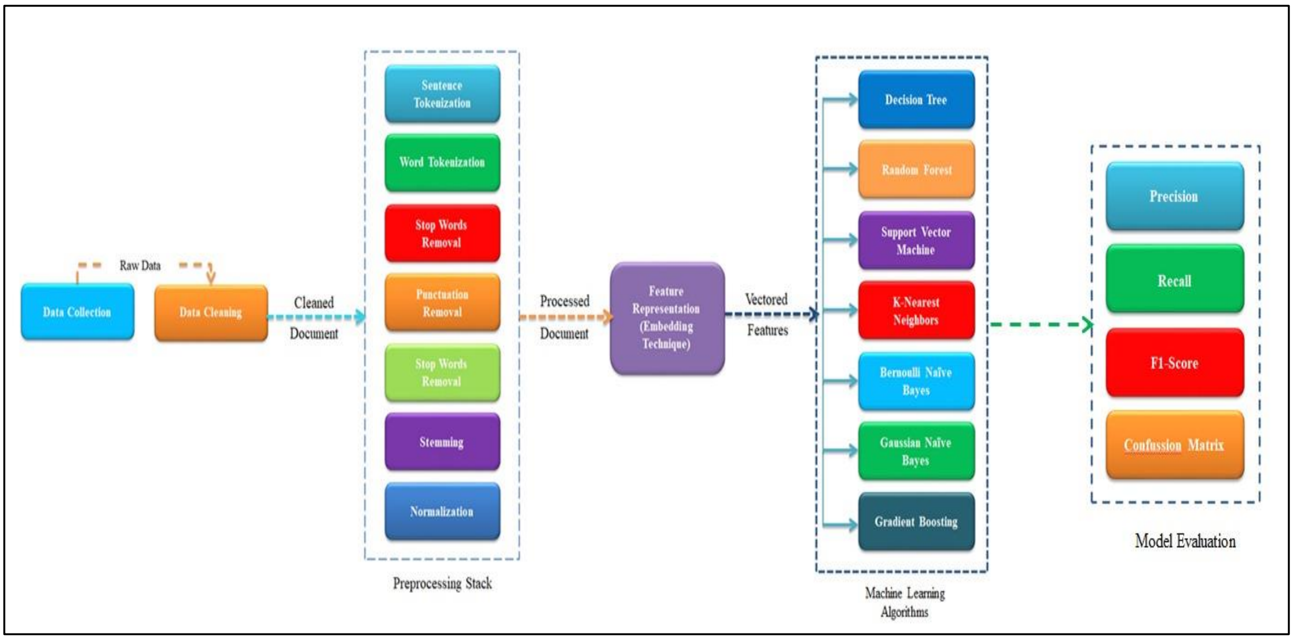

Figure 1. Method of Proposed System Model

Data Collection:

A CSV file containing the suicide dataset was taken from Kaggle. There are just two characteristics in this dataset. One of these is a column called "text" that contains the post's textual information, and the other is a column called "class" that indicates whether the user committed suicide or not. The Pushshift API was used to first extract the data. The dataset is interesting in that half of the messages are suicidal and the other half are not.

Data Preprocessing:

The authors verified that the dataset didn't include a null value before continuing with the data processing. Authors got rid of all the rows that had nothing in them by deleting them. The most pre-processing techniques were needed for the "text" feature. It's important to notice that the "text" column was subjected to all pre-processing methods in this case. ML models struggle when presented with nonsensical data. Extraneous characters are a major source of noise in data; hence it is crucial to remove them. This list may include special characters, emoticons, URLs, sentences, and other meaningless characters. The ability to manage terminology becomes crucial when working with textual material. With the aim of deleting just inflectional ends and restoring the lemma, or dictionary form, of a word, the authors did "Lemmatization" for this purpose in

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order to complete tasks properly utilizing vocabulary and morphological analysis of words. The authors also used “Word Shorten” or "Stemming," which is another pre-processing method. Stemming is a phrase that often refers to a crude heuristic technique that attempts to achieve this aim most of the time by removing derivational affixes from words. In order to simplify a word's inflectional forms and, rarely, associated derivational forms, lemmatization and stemming both attempts to do so.

Data Visualization:

An exploratory data analysis was performed on a dataset acquired from Kaggle including suicide records and the findings are visualized here. The visualizations draw attention to trends and patterns in suicide rates, providing valuable insights that may be used to develop effective strategies for preventing suicide. Understanding the complexities of suicide and identifying potentially susceptible demographics is made possible with this data collection.

Different suicidal cases are presented in the following figures. Fig. 2 represents suicides by causes in India. Fig. 3 identifies the Gender wise suicides occurs in India. Fig. 4 represents the means of committing suicide. State-wise suicidal cases are presented in Fig. 5 Causes of suicide is presented in Fig. 6.

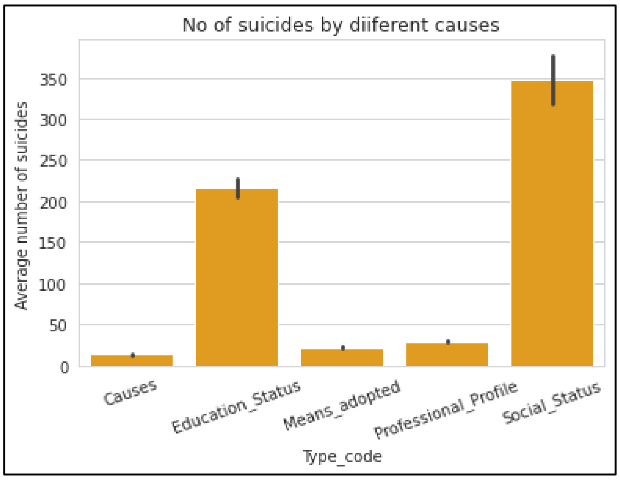

Figure 2. Suicides by Causes in India

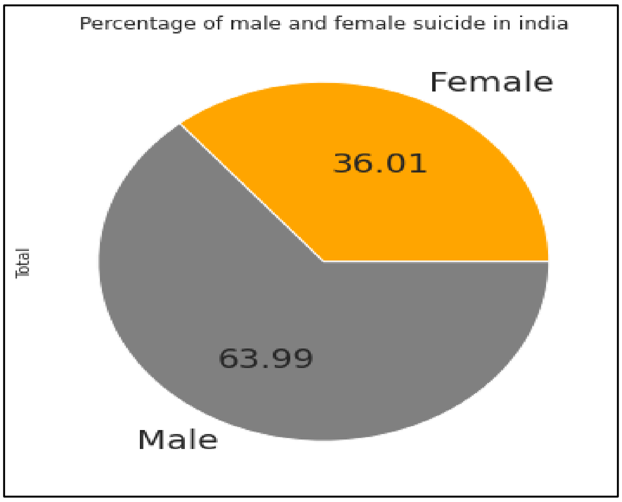

Figure 3. Suicides Occurs in India-Gender Wise

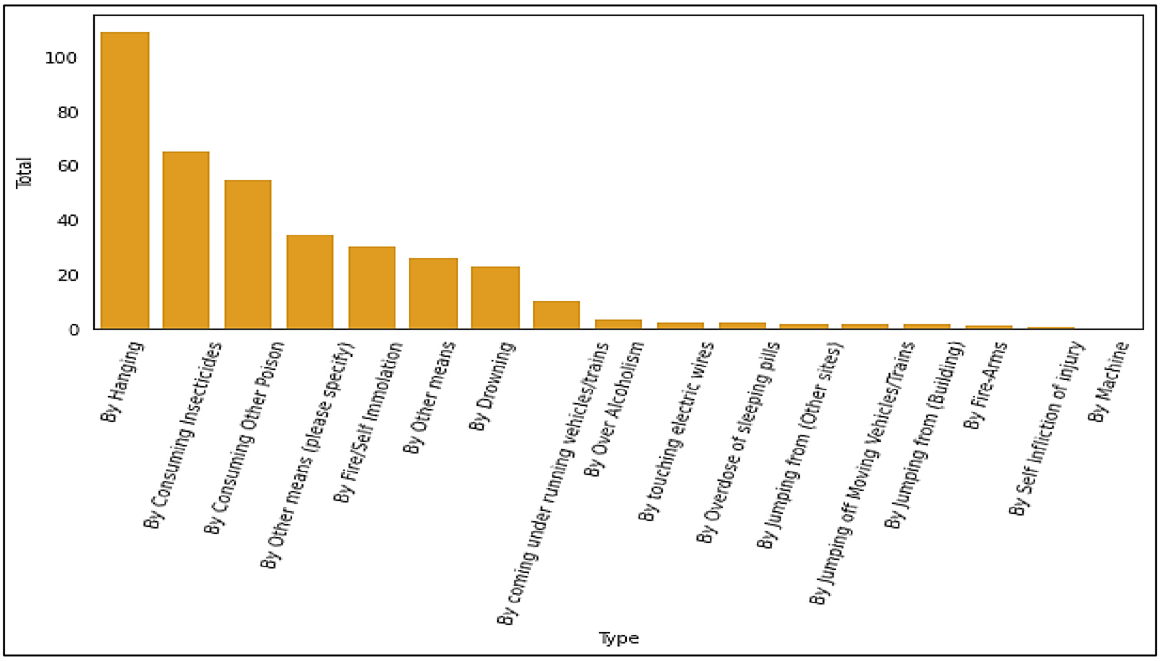

Figure 4. Means of Committing Suicide

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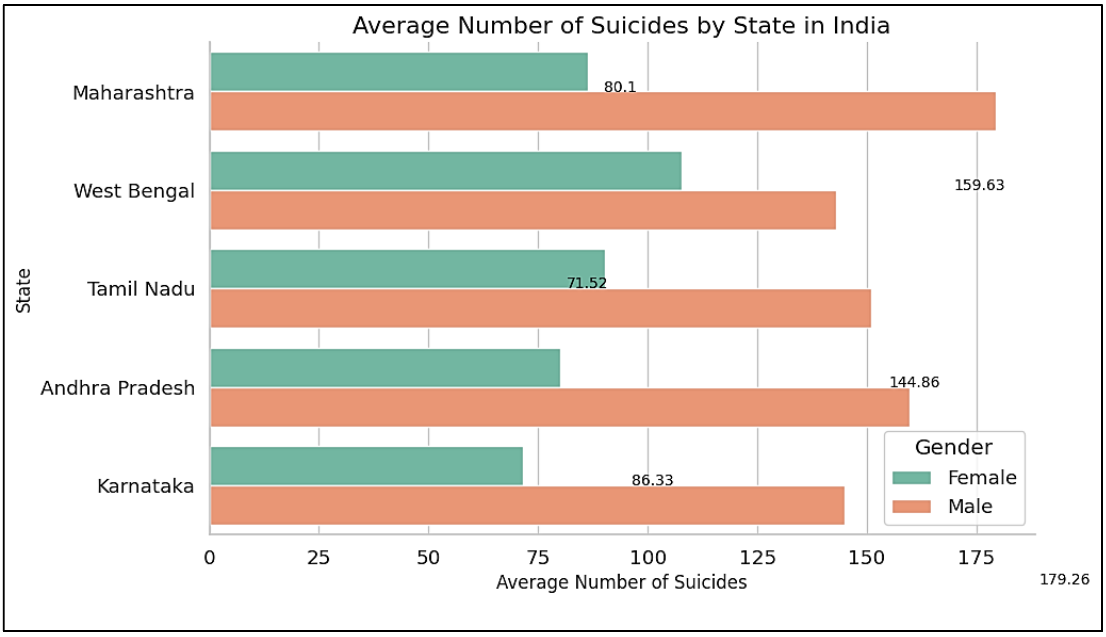

Figure 5. Suicidal Cases-State Wise

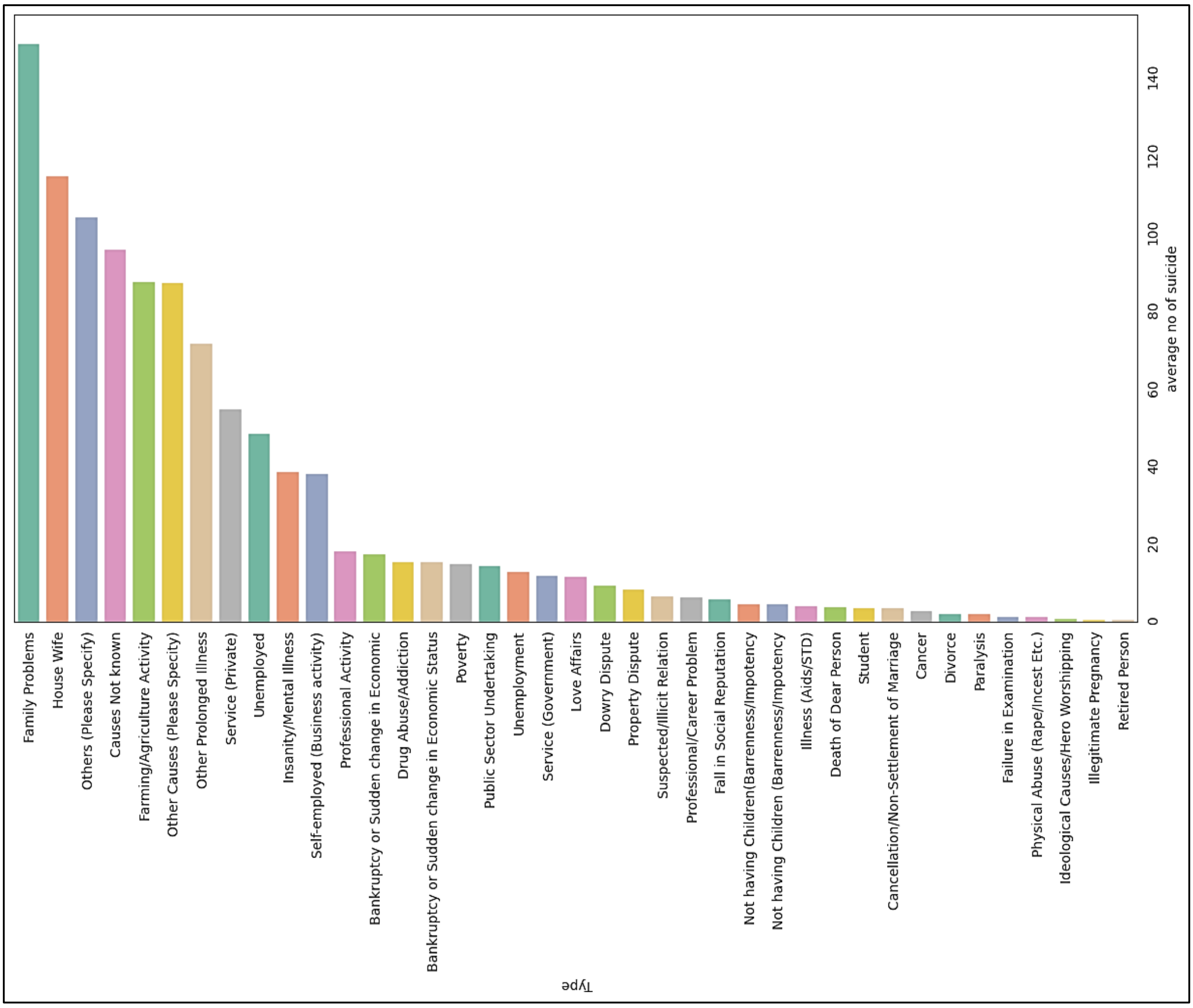

Figure 6. Different Causes of Suicide

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Feature Selection:

Finding and selecting the most important characteristics from a dataset is the aim of feature selection in machine learning in order to build a precise prediction model. Utilizing filter methods, wrapper methods, embedding techniques, etc., feature selection may be accomplished in several ways. The best feature selection strategy depends on the specifics of the dataset and the requirements of the present task.

For our research on spotting suicidal thoughts in social media postings, authors used a dataset with only two columns: the text and the suicidal state. The feature selection stage was not important in this case since the dataset already included the relevant information needed for classification. Our findings showed that the complexity of the dataset and the specific research goals have a major influence on the success of the feature selection process, and that this should be carefully considered when selecting the optimum feature selection approach.

Train and Test Data Generation:

The dataset was separated into train and test datasets prior to model training. The dataset was split into two parts: 20% was used to assess the models' performance and accuracy, and 80% was utilised to train our model.

Building and Training the Model:

Word embeddings are used to convert text documents into numerical vectors that may then be processed by machine learning techniques, so resolving our categorization problem. For each document in the dataset, the application creates a word vector using the Word2Vec embedding model that has already been trained. The document vectors are then used as input in a variety of machine learning classification algorithms. In order to prepare a dataset for machine learning, the software includes options to load the Word2Vec embedding model and vocabulary, to clean the text data, to generate document vectors, and to pre-process the whole dataset. Word embeddings may be used in document classification systems, and this code can be modified for use in other text classification tasks for researchers who are interested in this area.

The authors examined the complete pre-processed textual sample to determine lexical differences and suicidal thinking frequency. Authors computed unigram frequencies in suicidal and non-suicidal tweets. Python's Word Cloud visualization tool helped us understand the top 200 unigrams in each category and how they connect to suicidal thoughts. The top 200 unigrams from the dataset are shown in Fig. 7 a WordCloud as suicidal and non-suicidal tweets. Table 1 represents the word frequency.

Words like "fuck," "crap," "hate," "pain," "I'm exhausted," and "worthlessness" appear often in tweets with suicide intent, as do negation expressions like "don't want," "never," and "nothing," as shown by the Word Cloud of suicidal class. The authors found that words having suicide connotations ('death,' 'desire die,' 'kill') are indicative of the user's state of mind. Words like "I'm joyful," "want fun," "laugh loud," and "wonderful feel" are common in the non-suicidal postings' assessed unigrams, in contrast to the suicidal postings' "I'm sad" and "I'm angry" expressions. Additionally, users are more likely to actively endeavour to improve their outlook ("feel better") or participate in social activities ("work").

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Table 1. Word Frequency Table

Bigram	Count	Bigram	Count
(‘feel’, ‘like’)	1395	(‘die, ‘want’)	168
(‘want’, ‘die’)	742	(‘get’, ‘bad’)	152
(‘want’, ‘kill’)	300	(‘year’, ‘old’)	150
(‘want’, ‘end’)	271	(‘good’, ‘friend’)	146
(‘want’, ‘live’)	240	(‘get’, ‘well’)	143
(‘commit’, ‘suicide’)	212	(‘want’, ‘talk’)	141
(‘end’, ‘life’)	211	(‘need’, ‘talk’)	134
(‘suicidal’, ‘thought’)	205	(‘know’, ‘anymore’)	133
(‘need’, ‘help’)	195	(‘know’, ‘want’)	130
(‘go’, ‘kill’)	176	(‘know’, ‘feel’)	122

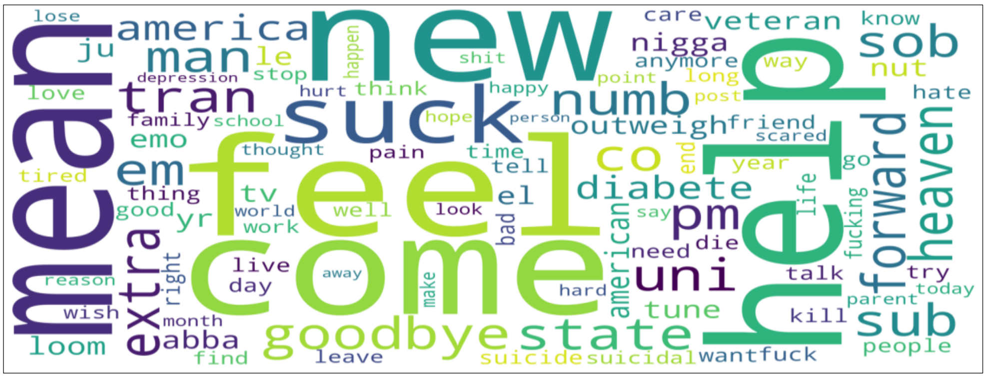

Figure 7. Sample WordCloud

Results and Discussion

Accuracy, precision, recall, and F1 score may be used to assess a Classifier. The quantity and quality of training data, the features employed, and the regularization intensity all affect logistic regression's effectiveness. Fig. 8 represents the suicidal text and non-suicidal text. Fig. 9 represents the decision boundary, support vector margin lines.

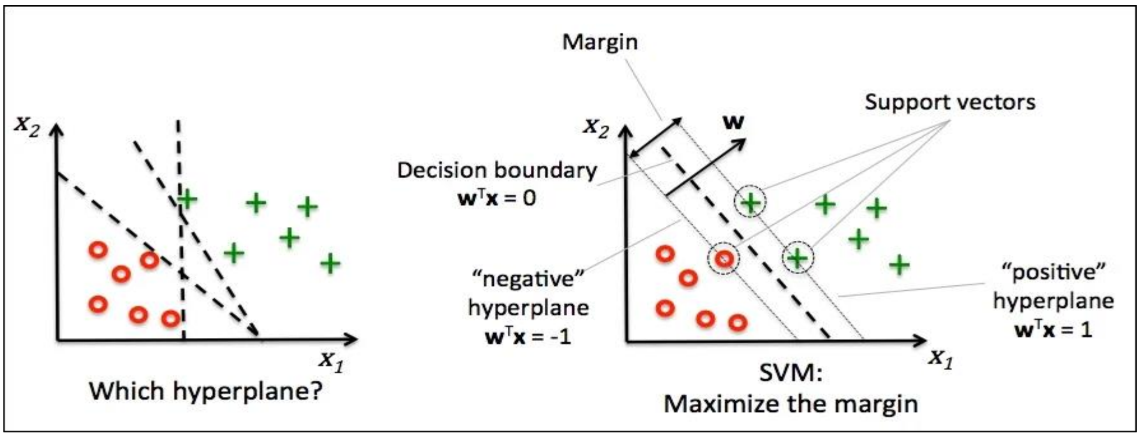

Figure 8. ‘0’-Non-Suicidial Text, ‘1’-Suicidal Text

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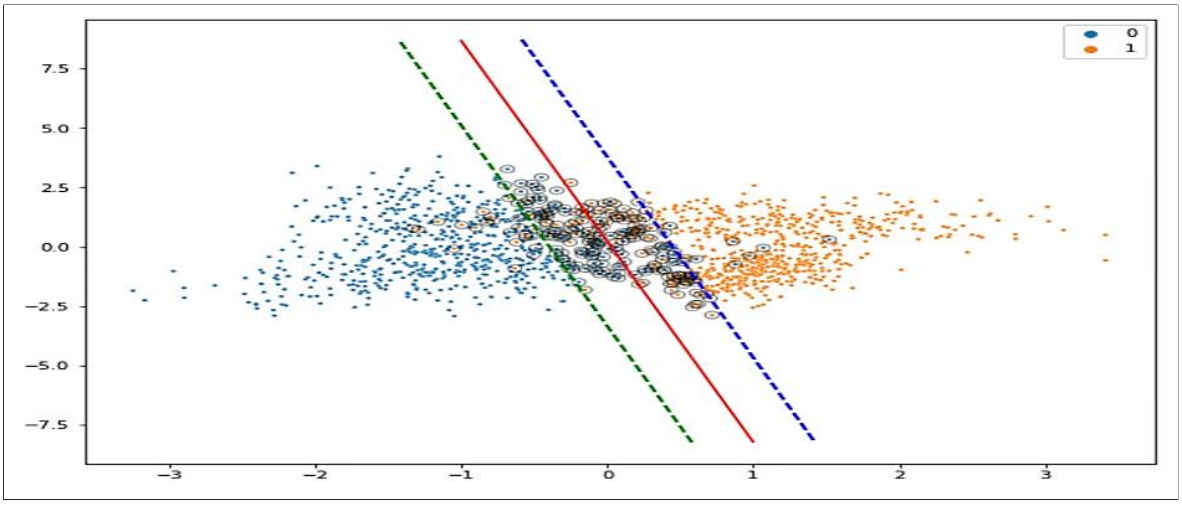

Figure 9. Decision Boundary (Red Colour), Support Vector (Encircled Dots), Margin Lines (Dashed Blue-Green Lines)

Figs. 10,11, and 12 represent the classification report of three different performance metrics, such as: SVM, Gradient Boosting, Naïve Bayes Classifier.

Support Vector Machine

	precision	recall	f1-score	support
0	0.90	0.91	0.91	2779
1	0.86	0.84	0.85	1774
accuracy			0.89	4553
macro avg	0.88	0.88	0.88	4553
weighted avg	0.89	0.89	0.89	4553

Figure 10. Classification Report of SVM Classifier

Gradient Boosting Classifier

	precision	recall	f1-score	support
0	0.93	0.79	0.85	2779
1	0.73	0.91	0.81	1774
accuracy			0.84	4553
macro avg	0.83	0.85	0.83	4553
weighted avg	0.86	0.84	0.84	4553

Figure 11. Classification Report of Gradient Boosting Classifier

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Bernoulli Naïve Bayes Classifier

	precision	recall	f1-score	support
0	0.93	0.79	0.85	2779
1	0.73	0.91	0.81	1774
accuracy			0.84	4553
macro avg	0.83	0.85	0.83	4553
weighted avg	0.86	0.84	0.84	4553

Figure 12. Classification Report of Bernoulli Naïve Bayes Classifier

Fig. 13, 14, 15 and 16 represent the classification report of other four different performance metrics, such as: Grad Gaussian Naïve Bayes, Decision Tree, K-Nearest Neighbors, Random Forest Classifier.

Grad Gaussian Naïve Bayes Classifier

	precision	recall	f1-score	support
0	0.92	0.84	0.87	2779
1	0.77	0.88	0.82	1774
accuracy			0.85	4553
macro avg	0.84	0.86	0.85	4553
weighted avg	0.86	0.85	0.85	4553

Figure 13. Classification Report of Grad Gaussian Naïve Bayes Classifier

Decision Tree Classifier

	precision	recall	f1-score	support
0	0.87	0.85	0.86	2779
1	0.78	0.80	0.79	1774
accuracy			0.83	4553
macro avg	0.82	0.83	0.83	4553
weighted avg	0.83	0.83	0.83	4553

Figure 14. Classification Report of Decision Tree Classifier

K-Nearest Neighbors Classifier

	precision	recall	f1-score	support
0	0.90	0.89	0.90	2779
1	0.83	0.85	0.84	1774
accuracy			0.88	4553
macro avg	0.87	0.87	0.87	4553
weighted avg	0.88	0.88	0.88	4553

Figure 15. Classification Report of K-Nearest Neighbors Classifier

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Random Forest Classifier

	precision	recall	f1-score	support
0	0.89	0.89	0.89	2779
1	0.83	0.83	0.83	1774
accuracy			0.87	4553
macro avg	0.86	0.86	0.86	4553
weighted avg	0.87	0.87	0.87	4553

Figure 16. Classification Report of Random Forest Classifier

Fig. 17 to 23 represent the Confusion Matrix of the said classifiers.

```
Confusion matrix:
[[2535  244]
 [ 275 1499]]
Classification report:
Accuracy: 0.8860092246870196
Recall: 0.8449830890642616
Precision: 0.8600114744693058
F1-Score: 0.8524310491896503
```

Figure 17. Confusion Matrix: Support Vector Machine

```
Confusion Matrix:
 [[2188   591]
 [ 155 1619]]
Accuracy: 83.62%
Recall: 91.26%
Precision: 73.26%
F1-Score: 81.28%
```

Figure 18. Confusion Matrix: Gradient Boosting Classifier

```
Confusion Matrix:
 [[2188   591]
 [ 155 1619]]
Accuracy: 83.62%
Recall: 91.26%
Precision: 73.26%
F1-Score: 81.28%
```

Figure 19. Confusion Matrix: Bernoulli Naïve Bayes Classifier

```
Confusion Matrix:
[[2475  304]
 [ 260 1514]]
Accuracy: 0.87612563145179
Precision: 0.8327832783278328
Recall: 0.8534385569334837
F1-Score: 0.8429844097995546
```

Figure 20. Confusion Matrix: Gaussian Naïve Bayes Classifier

```
Confusion matrix:
[[2349  430]
 [ 408 1366]]
Accuracy: 0.82
Recall: 0.77
Precision: 0.76
F1-Score: 0.77
```

Figure 21. Confusion Matrix: Decision Tree Classifier

```
Confusion Matrix:
[[2475  304]
 [ 260 1514]]
Accuracy: 0.87612563145179
Precision: 0.8327832783278328
Recall: 0.8534385569334837
F1-Score: 0.8429844097995546
```

Figure 22. Confusion Matrix: K-Nearest Neighbors Classifier

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```
Confusion Matrix:
 [[2476  303]
 [ 319 1455]]
Accuracy: 0.8633867779486053
Precision: 0.8276450511945392
Recall: 0.8201803833145435
F1-Score: 0.8238958097395245
```

Figure 23. Confusion Matrix: Random Forest Classifier

The results support the idea that several different machine learning algorithms may greatly enhance suicide detection and prevention efforts. Gradient Boosting Classifier, Decision Trees, K-Neighbors Classifier, Random Forest, SVM, and Gaussian and Bernoulli Naive Bayes were among the six methods employed in our research. Each technique was evaluated based on several different classification criteria, including accuracy, precision, recall, and F1-score. Our findings showed that all algorithms were successful, with SVM having the highest accuracy, i.e., 88.6% , and Gaussian Naive Bayes having the best precision i.e.,77.3%.

Our study demonstrates the potential of machine learning algorithms as a screening tool for identifying people who are suicidal by detecting suicidal thoughts. The results also suggest that machine learning algorithms might be used with existing suicide prevention strategies. Therefore, our work contributes to the expanding body of information on the efficacy of machine learning in suicide prevention and highlights the necessity for further investigation into the use of these algorithms in clinical settings.

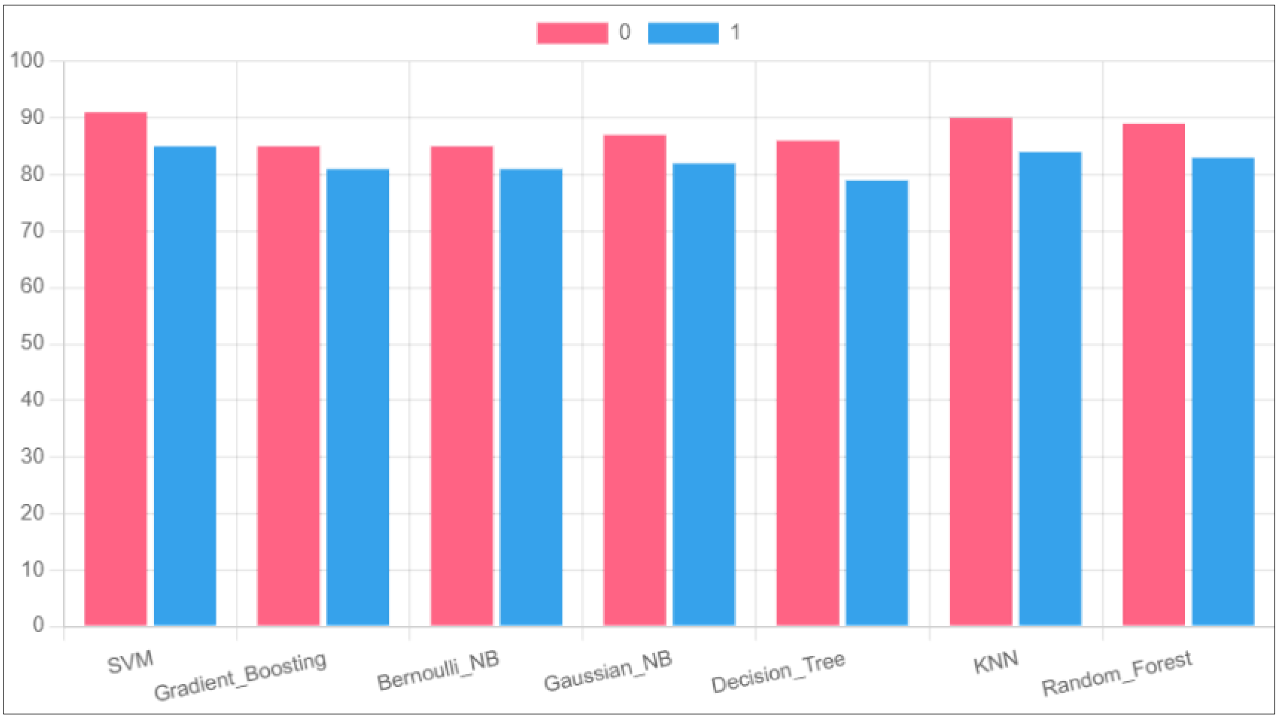

Figure 24. Comparison of F1-Score of all classifiers.

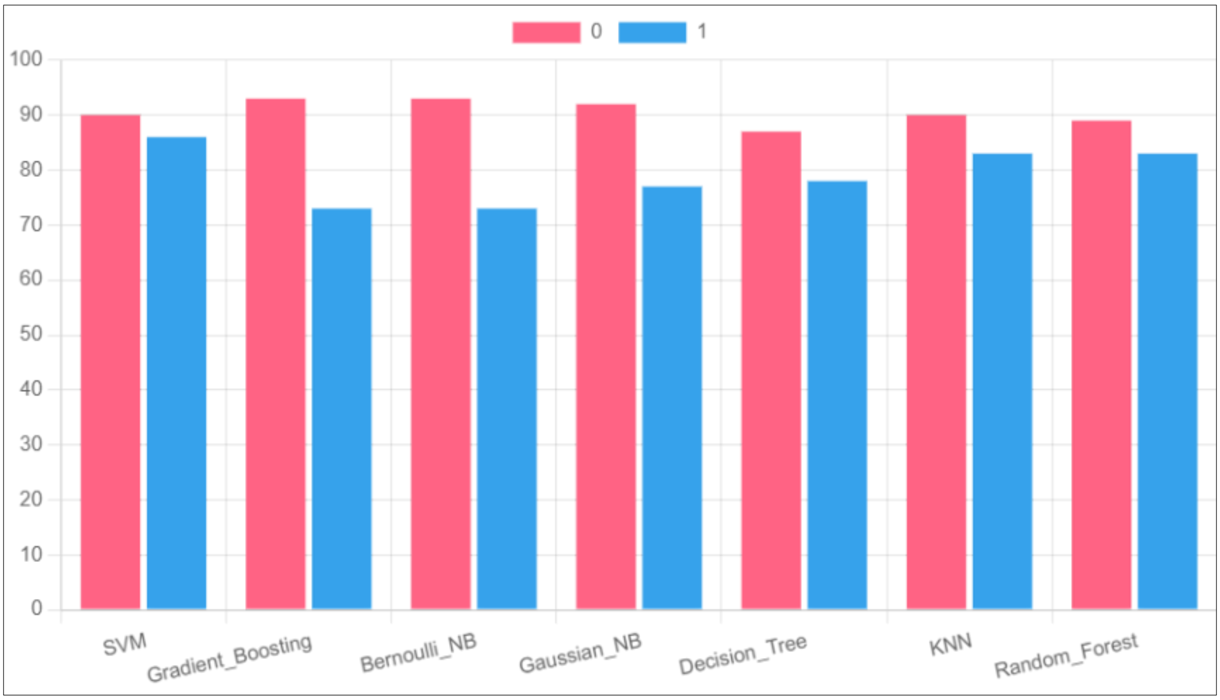

Figure 25. Comparison of Precision of all of classifiers.

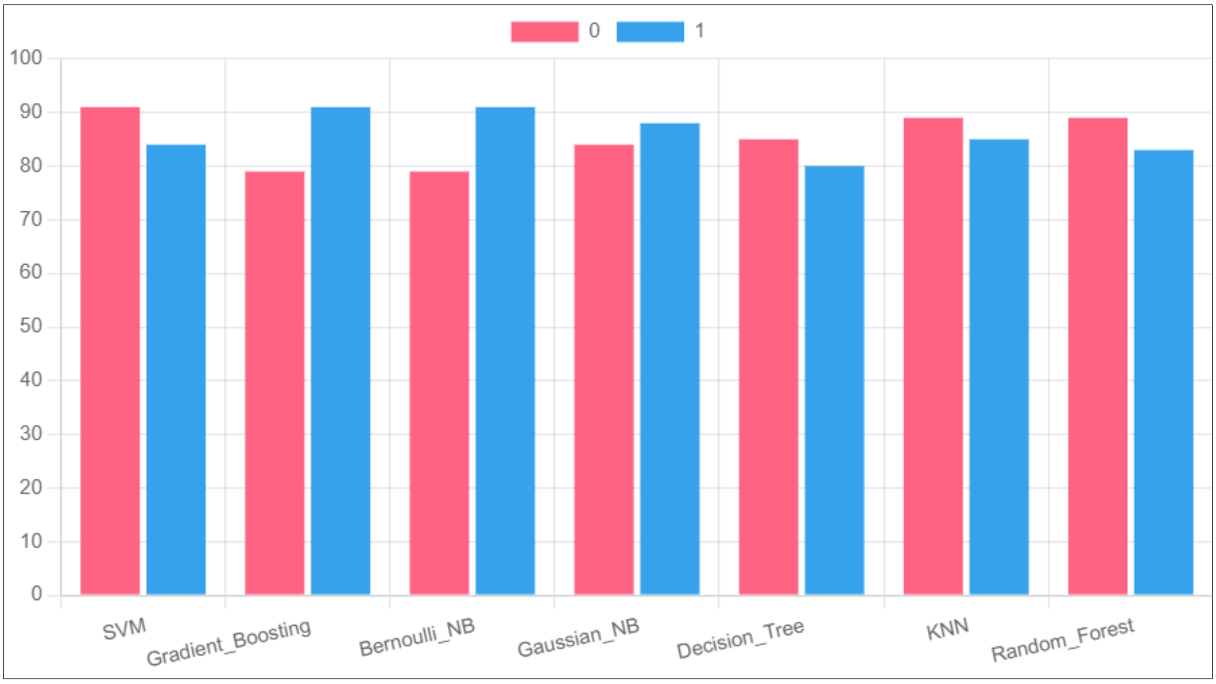

Figure 26. Comparison of Recall of all of classifiers.

After representing the different classification reports, authors have presented the accuracy of different classifiers in Fig. 27.

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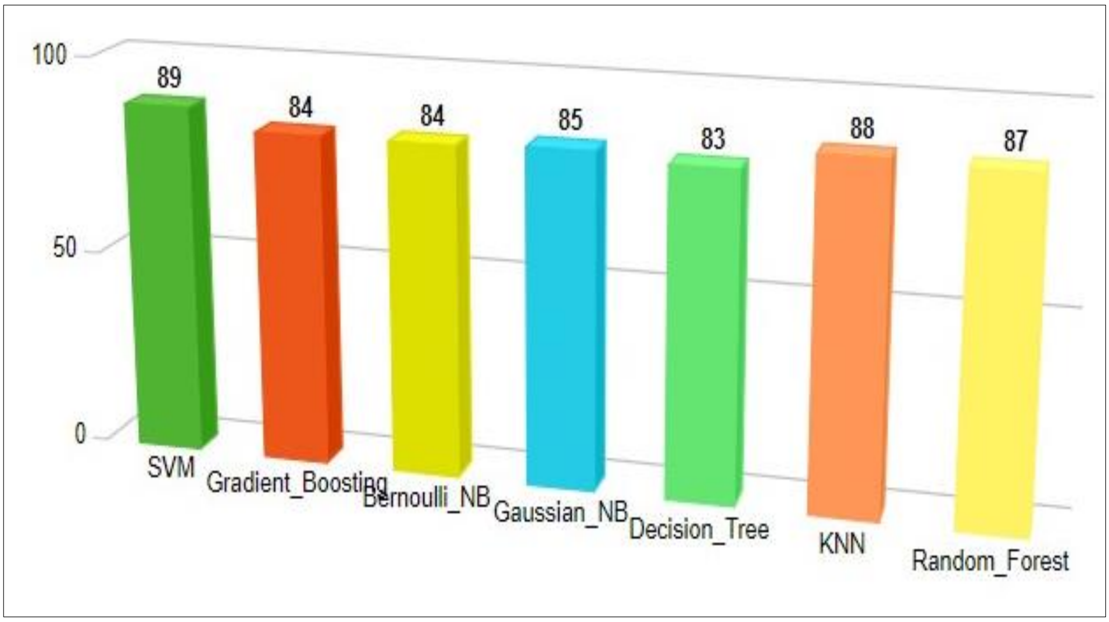

Figure 27. Comparison of Accuracy of Different Classifiers

Upon experimenting out several machine learning classifiers, authors found that all of them provide satisfactory results on the provided training data. The Support Vector Classifier, however, has outperformed all other models using the provided data and is without a doubt the most useful model for this problem statement. To discover the optimal settings for the SVM Classifier model, authors employed the GridSearchCV() function to do trial and error experiments with the parameter values. The ideal values are "C": 10, "gamma": "scale," and "kernel": "rbf."

Conclusion

Suicide is a multifaceted, multicultural public health crisis that affects people of all demographics. Early detection of suicidal ideation is a crucial and effective method for reducing suicide rates. Detecting suicidal thoughts on social media sites like Twitter sooner rather than later would help doctors spot and treat many more cases of suicide attempt. World Health Organization data show that suicide is the second leading cause of mortality and the leading cause of disability. It is difficult to draw definitive conclusions on suicide since it is such a complex, multifaceted topic that may be impacted by a wide variety of factors. Suicide is a major issue in public health that cuts across demographics in terms of age, gender, and ethnicity. Several methods exist to prevent suicide and help those who are in risk. By limiting access to fatal means, encouraging social interaction and a feeling of community, and educating the public about the warning signs of suicide and how to assist individuals who may be in danger, policies and initiatives are being implemented to lower the risk of suicide. One of these is expanding access to mental health services for those who need help dealing with mental health issues. Policies and programs are being put in place to reduce the risk of suicide by restricting access to lethal methods, fostering social connection and a sense of community, and educating the public about the warning signs of suicide and how to help those who may be in danger. People between the ages of 15 and 24 must carefully address the issue of young suicide. Given that this age group is particularly susceptible to suicide, efforts at early detection and prevention are crucial. The authors can work to lower suicide rates and save lives by implementing evidence-based preventative initiatives and increasing access to mental health care.

Author's Declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are mine/ours. Furthermore, any Figures and images, that are not ours, have been included with the necessary permission for re-publication, which is attached to the manuscript.
- Ethical Clearance: The project was approved by the local ethical committee in JIS College of Engineering.

Author's Contribution Statement

A. A. and R. S. contributed to the conceptualization of the paper, acquisition of data, and interpretation of the findings. S. S. conducted the analysis of the data, interpreted the results, drafted the manuscript, and participated in the revision process. S. D. G. conducted analysis, contributed to the interpretation of the findings, participated in the revision process, and assisted with proofreading. S. N. contributed to the analysis and interpretation of the data. S. D. participated in the revision process and provided proofreading assistance.

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تحقيق في الأفكار الانتحارية من وسائل التواصل الاجتماعي باستخدام طريقة التعلم الآلي

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الخلاصة

على الرغم من التحسينات في الكشف عن الاضطرابات النفسية الشديدة وعلاجها ، لا يزال الانتحار مصدر قلق كبير للصحة العامة. يمكن أن تستفيد مبادرات منع الانتحار ومكافحته بشكل كبير من الفهم الشامل والتنبؤ بأنماط الانتحار. يمكن أن يساعد فهم أنماط الانتحار ، وخاصة من خلال تحليل بيانات وسائل التواصل الاجتماعي ، في جهود منع الانتحار والسيطرة عليه. الهدف من هذه الدراسة هو تقييم تنبؤات السلوك الانتحاري لدى البشر باستخدام التعلم الآلي. من الأهمية بمكان إنشاء نموذج للتعلم الآلي للكشف عن أفكار الانتحار من خلال مراقبة منشورات المستخدم على وسائل التواصل الاجتماعي لتحديد علامات التحذير من مشاكل الصحة العقلية. من خلال تحليل منشورات وسائل التواصل الاجتماعي ، يهدف بحثنا إلى تطوير نموذج للتعلم الآلي لتحديد الأفكار الانتحارية ومشاكل الصحة العقلية المحتملة. ستساعد هذه الدراسة بشكل كبير على فهم عوامل الخطر البيئية التي تؤثر على الأفكار والسلوك الانتحاري عبر الزمن. في هذا البحث ، يعد استخدام التعلم الآلي على بيانات الوسائط الاجتماعية اتجاهًا جديدًا مثيرًا لفهم عوامل الخطر البيئية التي تؤثر على قابلية الفرد للتفكير في الانتحار والسلوك بمرور الوقت. أظهرت خوارزميات التعلم الآلي دقة عالية ودقة واستدعاء ودرجة F1 في الكشف عن أنماط الانتحار على بيانات وسائل التواصل الاجتماعي ، في حين أن SVM لديها أعلى أداء بدقة تبلغ 0.886.

الكلمات المفتاحية: السلوك ، التفكير ، التعلم الآلي ، التنبؤ، وسائل التواصل الاجتماعي ، الانتحار.