Detection of Suicidal Ideation on Social Media using Machine Learning Approaches

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ABSTRACT
Early detection and prevention in suicide cases are crucial for saving lives, as timely interventions can reduce the risk of self-harm. Identifying individuals at risk before an incident occurs is a challenging task. The growing use of social media offers unique insights into individuals' behaviours like thoughts, feelings, and intentions. Therefore, this study is essential as understanding effective methods for identifying and preventing suicide can help address a major public health concern and save lives. This research addresses the use of machine learning (ML) models for identifying suicide cases and conversely, preventing them based on social media posts. In this paper, six ML classifiers, including Support Vector Machine (SVM), Naive Bayes (NB), Random Forest (RF), Logistic Regression (LR), Decision Tree (DT), and XGBoost (XGB), are employed for the classification task using social platforms data analysis. The proposed ML model's performances are evaluated using the publicly available datasets from the Kaggle and Reddit. Compared with all the other ML models SVM shows as the top performer with an accuracy of 93.85%, precision of 93.86%, recall of 93.85%, and an F1-score of 93.85, whilst the LR classifier achieved almost similar results. On the other hand, the DT classifier gained lowest classification performances. The study signifies that the effectiveness of the proposed ML approach in classifying nuanced mental health-related content, contributing to ongoing efforts in suicide prevention through advanced computational methods.

Keywords
Suicide Ideation, Text Classification, Machine Learning, Social Media Platforms, Suicide Prediction.

1. INTRODUCTION
The rapid growth of social media has become an integral part of global communication, connecting billions of individuals worldwide. The total number of social media users reached around 4.72 billion in January 2023, up from 4.62 billion in January 2022. It shows a significant 3% yearly growth, adding about 137 million new users [1]. Social media usage presents unique opportunities and challenges, especially in the context of mental health concerns such as depression and suicide sentiment [2]. Social media platforms such as Facebook, Tweeter and blogs constantly advancing to meet different needs, including entertainment, communication, advertising, business, and education. It becomes crucial to explore the relationship between social media usage and users with suicide sentiment [3] [4].

Despite the widespread positive impact of social media, there is a growing concern about the manifestation of suicidal thoughts and intentions on these platforms [5], [6]. As individuals express emotions like emotion, depression and happiness on social media, it is crucial to understand and predict suicidal thoughts [7] from their communication patterns before any incident occurs for saving lives. Suicide is a global public health issue, affecting over 7 million individuals annually, with profound consequences for families, communities, and entire nations. In 2019, suicide ranked as the 4th leading cause of death among 15-29 year olds people globally [8], whilst it's become 3rd in 2021 [9]. Hence, research on this domain is essential due to the growing concern over suicidal thoughts expressed on social media, and the alarming rise in suicide rates, particularly among young people, making it a global public health issue.

Machine learning (ML) has emerged as a valuable tool for addressing the complex challenge of suicide prediction. Leveraging various ML algorithms (or classifier), including Naive Bayes (NB), Random Forest (RF), and Support Vector Machines (SVM), XGBoost, Decision Tree (DT) and Logistic Regression (LR), data patterns can be analyzed to make predictions (or classification) based on data from social platforms. In this study, the dataset is collected from the Kaggle and Reddit, which are publicly available for the research community. The primary objective of this study is to develop a supervised ML model capable of identifying individuals at risk of suicide, enabling timely interventions and potentially saving lives. Despite the increasing relevance of ML in suicide prediction, there are exists some gaps in research concerning the integration of specific ML algorithms for this purpose. This study aims to bridge those gaps by providing a comprehensive exploration of different ML models in the context of suicide sentiment prediction on social media. Experimental results indicate that the proposed ML model shows higher performances, whilst the SVM classifier shows as the top performer with an accuracy of 93.85% using the state-of-the-art dataset. In contrast, the DT classifier recorded the lowest classification performances with an accuracy of 85.5%. The key contributions of this research work are:

a. Proposing an ML based model for detecting suicidal ideation through the analysis of data from online platforms such as social media. By leveraging ML techniques, a model is aimed to be developed that can effectively identify suicidal ideation through the analysis of social media data.
b. Different supervised ML algorithms, including SVM, NB, RF, LR, DT, and XGBoost, are utilized to evaluate the performance of the proposed model on a benchmark dataset.
c. Investigating textual data from social media platforms using TF-IDF technique for transforming textual data into numerical representations forms, exploring its efficacy in capturing semantic information.

The rest of the paper is organized as follows: Section 2 provides a brief overview of related works. Section 3 outlines the proposed suicidal ideation model, including dataset and preprocessing steps, as well as traditional machine learning algorithms. Section 4 presents the experimental findings, limitations, and suggests future directions for the research. Finally, Section 5 concludes with a summary of the key findings.

2. RELETED WORK

Researchers [10], [11], [12] in the same domain have proposed various suicidal ideation models using different ML or deep learning approaches by analysing textual data from social media platforms. These models aim to accurately identify suicidal ideation from a large pool of information. Table 1 provides a brief description of the existing models.

Chatterjee et al. [11] presented a ML based suicide ideation detection model using Twitter data analysis, aiming to prevent suicide attempts. The researchers utilized various natural language processing (NLP) and statistical techniques, including latent Dirichlet allocation (LDA), trigrams, term frequency-inverse document frequency (TF-IDF), tweet statistics, emoticons, temporal sentiments, and sentiment analysis, to extract features from 188,704 English tweets by 1,169 users. The model achieved over 87% accuracy and an 81% F1-score using the LR classifier, highlighting the importance of feature selection approaches in enhancing performance for identifying potential suicidal ideations on social media.

Table 1. Existing research works

Source	Objective/ Problem	ML	Social Media Platform (Dataset)
[11]	Suicide Posts Prediction/ Identification	LR, SVM, RF, XGBoost	Twitter
[10]		XGBoost, CNN–BiLSTM	Reddit
[12]		RF, SVM, NB, CNN, LSTM, and BERT	Twitter
[13]		LSTM-Attention-CNN, SVM	Reddit
[14]		SVM, BN, LR, SASS	Twitter
[15]		J48, RF, LR, NB, Bagging, Stacking, Logistic Regression	Twitter
[16]		NB, K-KNN, CNN	Facebook, Twitter, blogs, forums, and magazines.
[17]		J48, CART, NB	Twitter

Note: Twitter – It is one of the world's largest social networks, where users can share text messages, images, videos, and more through posts. Reddit – It is home to thousands of communities that foster endless conversations and authentic human connections, covering interests from breaking news, sports to TV fan theories, and more through direct or indirect posts.

Aldhyani et al. [10] proposed an automated system for early detection of suicidal ideation on social media, utilizing word-embedding techniques such as TF-IDF and Word2Vec for text representation. They employed a hybrid deep learning (DL) approach, Convolutional Neural Network–Bidirectional Long short-term memory (CNN–BiLSTM), and a traditional ML approach, XGBoost, to evaluate the performance of their model on the Reddit dataset (Suicide and depression detection dataset, collected from the Kaggle). Experimental results demonstrated that the model achieved 95% accuracy in detecting suicidal ideation using the CNN–BiLSTM classifier. In reference [12], the researchers proposed an ML-based suicidal ideation model to identify suicidal and non-suicidal posts. Social platforms such as Twitter, Facebook, Reddit, and Suicide Watch were used to collect user posts (data) for analysis, incorporating statistics, word-based features, TF-IDF, longest inquiry word count (LIWC), semantics, and syntactics. Both traditional ML and DL approaches employed to evaluate the models' performance. Experimental results demonstrated that the bidirectional representations from transformers (BERT) model achieved the highest accuracy at 92%.

Renjith et al. [13] introduced an ensemble DL technique for detecting suicidal ideation from social media posts, addressing the challenges of identifying complex risk factors and warning signs. Their model, combining LSTM, Attention, and CNN, achieved a notable accuracy of 90.3% and an F1-score of 92.6% using the Reddit dataset. Additionally, the inclusion of the SVM model in the experiment demonstrated its effectiveness with an accuracy of 82.5%, highlighting the significance of utilizing diverse ML approaches for robust detection of suicidal intentions on social media platforms. Rajesh et al. [14] introduced a mathematical model that enhances sentiment analysis for suicide prediction in microblogs by incorporating social and topic context. The authors used various ML classifiers, including SVM, NB, and LR, along with mathematical approaches like sentiment analysis based on structure similarity (SASS) and SASS-subject context (SASS-T), to evaluate performance on Twitter datasets (Dataset1 comprising microblog posts, and Dataset2 based on keywords). Their proposed SASS-T model achieved over 82.1% accuracy on the Twitter datasets, with 90% of the data used for training.

In reference [15], the researchers introduced a suicidal ideation model based on the analysis of Twitter data, employing various ML classifiers such as J48, RF, LR, and NB to evaluate model performance. TF-IDF and Bag of Words were used for feature extraction from the raw dataset, followed by significant feature identification using the InfoGainAttributeEval and Ranker algorithms in the Weka tool. The RF model achieved over 98% accuracy on the Twitter dataset using binary classification to distinguish between suicidal and non-suicidal tweets. Boukil et al. [16] introduced a DL-based model to predict or identify suicide-related sentiments, aiming to automate depression detection through sentiment analysis of online contents on Arabic language. The researchers utilized TF-IDF technique for generating feature matrix. Experimental results demonstrated significant performance using the CNN architecture. The proposed CNN model achieved a precision of 82.14%, a recall of 75.27%, and an F1-score of 79.07%, surpassing traditional models such as NB and K-KNN, whilst the dataset was manually collected from various online sources, including Facebook, Twitter, blogs, forums, and magazines.

Birjali et al. [17] addressed the challenge of predicting suicidal sentiments on social media platforms through a comprehensive approach. They combined the creation of a suicide-related vocabulary, ML algorithms like SVM (with the sequential minimal optimization (SMO) optimizer), J48, CART, and NB, along with semantic sentiment analysis. The sentiment analysis was performed based on WordNet. Twitter4J is utilized to collect tweet data automatically for building the dataset. The SMO model showed high performance, achieving 89.5% precision for tweets with suicide risk and 70% precision for those without suicide risk.

From the literature study, it has been observed that many researchers have been proposed various approaches using different ML, DL and mathematical models to identify suicidal sentiments (or posts) from social platforms. These studies utilized diverse datasets in multiple languages to evaluate model performances. Despite notable progress, challenges remain, particularly in improving classification accuracy and handling language variations effectively. Addressing these issues is crucial for advancing the accuracy and reliability of suicidal sentiment detection models.

3. PROPOSED METHODOLOGY

3.1 Dataset and Preprocessing

The dataset is collected from Kaggle [18] and Reddit [19], consisting of posts from the SuicideWatch and depression subreddits on Reddit. Pushshift API [20] is employed for collecting data. The dataset covers a long period, with SuicideWatch posts from December 16, 2008, to January 2, 2021, and depression posts from January 1, 2009, to January 2, 2021. All posts from the SuicideWatch are explicitly labelled as "suicide", whilst posts from the depression subreddit are marked as "depression". Additionally, non-suicidal posts are gathered from the 'r/teenagers' subreddit. The dataset is structured with two key columns: text and class/label, indicating the post content for sentiment analysis and the respective labels for suicide or non-suicidal categorization, respectively. This comprehensive dataset serves as a valuable resource for the research aimed for understanding sentiment and classifying posts related to mental health based on online platforms.

Table 2: Summary of the dataset

Specification	Value	Specification	Value
Total Sentences	232,010	Unique Tokens	145,389
Total Tokens	13,880,619	Average Length	59.83
Corpus Size	145,389	--	--

The dataset went through a series of essential transformations to enhance its suitability for analysis. Unwanted contents, including null values, URLs, special characters, single characters and numeric values, are removed from the dataset to improve clarity and noise free data. Subsequently, all text data are converted into lowercase for consistency. After that natural language toolkit (NLTK) [21] was employed for tokenization, and stop-words like and, the, is, etc removed from the textual content. A brief description of the dataset is presented in Table 2. The dataset contains 232,010 sentences and 13,880,619 tokens. The number of unique tokens is 145,389, with an average sentence length of 59.83 tokens in the corpus. The corpus with its optimized structure and valuable information serves as a key resource for sentiment analysis and classification tasks.

3.2 Machine Learning Algorithms

In this research, various ML algorithms are utilized to analyze and classify social media posts related to mental health. The algorithms employed include SVM, NB, RF, LR, DT, and XGBoost. ML classifiers/algorithms are utilized for various purposes, such as device classification [22], [23], [24], [25], [26], [27], anomaly detection [28], [29], [30], image classification [31], [32], medical science [33], [34], recommendation system [35], and education [36], [37]. A brief description of each algorithm is provided as follows.

- Support Vector Machine (SVM): SVM seeks to find a hyperplane that optimally separates different classes in the feature space. The decision function is represented by $f(x) = \text{sign}(w \cdot x + b)$, where w is the weight vector, x is the input vector, and b is the bias term [38].
- Naive Bayes (NB): NB is a probabilistic algorithm based on Bayes' theorem. It calculates probabilities by assuming independence between features. It is particularly effective for text classification tasks due to its simplicity and efficiency [39].
- Random Forest (RF): RF is an ensemble learning method that constructs multiple decision trees during training. The final prediction is based on the mode of the classes predicted by individual trees [40].
- Logistic Regression (LR): LR is a linear model used for binary and multiclass classification tasks. It calculates the probability of a class label using a logistic function based on the input features [41].
- Decision Tree (DT): DT is a tree-like model where each node represents a feature, and each branch represents the outcome of a decision based on that feature. It recursively splits the data to create a tree structure [42].
- XGBoost: XGBoost is an optimized distributed gradient boosting library designed for speed and performance. It efficiently builds a series of DTs to make predictions [43].

3.3 Feature Engineering

In this study, textual data are transformed into numerical values that reflect the importance of each term in a document compared to the whole dataset. A concise and informative feature set is generated using the scikit-learn library's [44] TfidfVectorizer [45] with a max_features constraint of 5000. A TfidfVectorizer is created with the following setting: *tfidf_vectorizer = TfidfVectorizer(max_features = 5000),* whereas T defines a set of unique terms across all documents. Subsequently, *TF-IDF* score is calculated as: $TF\text{-}IDF(t_j, d_i, D) = TF(t_j, d_i) \times IDF(t_j, D)$, whilst a collection of pre-processed documents is denoted as D, t_j represents unique terms in a document d_i, and d_i defines individual document in D. The term frequency $TF(t_j, d_j)$ is calculated as:

$$TF(t_j, d_i) = \frac{Number\ of\ occurrences\ of\ \ t_j\ in\ d_i}{Total\ number\ of\ unique\ terms\ in\ d_i}$$

The inverse document frequency $IDF(t_j, D)$ is calculated as:

$$IDF(t_j, D) = log\left(\frac{Total\ number\ of\ documents\ in\ D}{Number\ of\ documents\ containing\ t_j}\right) + 1$$

Finally, use the vectorizer on the preprocessed documents to get the TF-IDF matrix V as V = *tfidf_vectorizer.fit_transform(D)*. The resulting matrix V has dimensions $/D/ \times /T/$, representing the TF-IDF scores for each document d_i and term t_j.

3.4 The Proposed Model

An abstract design of the proposed architecture is depicted in Figure 1, whereas raw datasets are collected from publicly available data sources. Raw data can be captured manually or automatically from various social media platforms. In the preprocessing steps like removing URLs, symbols, stop-words, and tokenizing are applied to prepare the data for further analysis. After that, preprocessed data are utilized for feature extraction process, whilst TD-IDF approach's is employed for generating data matrix. Finally, the resulting data matrix is used as input for supervised machine learning classifiers like SVM, DT, RF, and NB to evaluate classification performance.

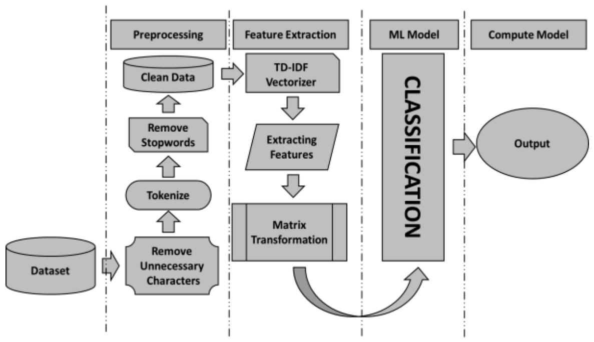

Fig. 1: An abstract workflow of the proposed approach

4. RESULTS AND DISCUSSION

The performance of the proposed suicidal ideation model has been evaluated on a Windows machine equipped with an Intel Core i7 processor, 16 GB of RAM, and a 2.0 GHz clock speed. Python (version 2.7) was used as the programming language for implementing the model, as it includes most of the libraries necessary for ML and data mining techniques. A benchmark publicly available dataset from Kaggle (Suicide and Depression Detection dataset) [10] was utilized for the evaluation.

4.1 The Proposed Model

The classification performance of the proposed supervised ML model is evaluated using various standard evaluation metrics [23], [25], [26], including accuracy (it represents the proportion of correctly predicted instances out of the total instances), precision (it represents the proportion of true positive predictions relative to the total predicted positive instances), recall (it represents the proportion of true positive predictions relative to the total actual positive instances), and F1-score (it defines the harmonic mean of precision and recall). These metrics are presented as follows:

$$Accuracy = \frac{Correct\ Predictions}{Total\ Predictions} \tag{1}$$

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{2}$$

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \tag{3}$$

$$F1\text{-}score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{4}$$

where true positives represent the total number of positive instances correctly classified, true negatives represent the total number of negative instances correctly classified, false positives represent the total number of negative instances incorrectly classified, and false negatives represent the total number of positive instances incorrectly classified.

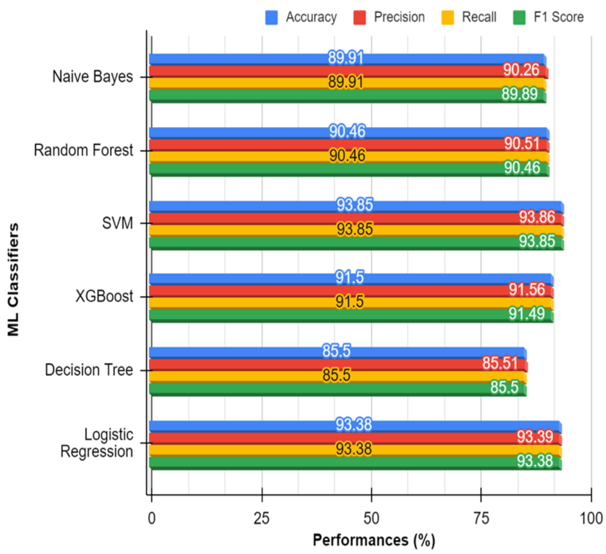

Fig. 2: Classification performances of the proposed ML models

4.2 Experimental Results and Discussion

All the experimental results from different ML approaches, including SVM, NB, RF, LR, DT, and XGBoost, for classifying mental health-related posts are presented in Figure 2. The NB classifier demonstrated commendable performance, with an accuracy of 89.91%, precision of 90.26%, recall of 89.91%, and an F1-score of 89.89%. On the other hand, the RF classifier exhibited almost similar performance, achieving over 90.46% in accuracy, precision, recall, and F1-score. As shown in Figure 4, the SVM model outperformed the other ML approaches, achieving an accuracy of 93.85%, precision of 93.86%, recall of 93.85%, and an F1-score of 93.85%. Conversely, the DT classifier demonstrated the lowest classification performance, not exceeding 85.51%. However, the XGBoost and LR classifiers performed significantly better than the DT classifier. The XGBoost classifier demonstrated robust performance, with an accuracy of 91.50%, precision of 91.56%, recall of 91.50%, and an F1-score of 91.49%, while the LR classifier achieved over 93.38% across all evaluation metrics. This comprehensive evaluation provides insights into the diverse performance of these supervised ML approaches, highlighting the nuanced trade-offs between accuracy, precision, recall, and F1-score in the context of classifying mental health-related posts from social media platforms. Overall, the results underscore the effectiveness of each ML model in capturing the complexities of mental health-related content.

4.3 Limitations and Future Works

Some of the key limitations of the proposed approach for classifying mental health-related posts from social media platforms using ML classifiers are presented in this section, as follows:

- The generalization of findings may be constrained by the specificity of the publicly available datasets, which are primarily collected from Kaggle and Reddit.
- Languages and expressions, including English, Bangla and others, used in these platforms may differ significantly from other online platforms as well as in real-life scenarios.
- The dataset's may not fully capture or record evolving language trends or emerging mental health-related phenomena, potentially affecting the model's ability to adapt to new linguistic patterns.
- The inherent subjectivity and variability in labeling the selected posts as 'suicidal' or 'depressive' pose challenges, as the interpretation of such labels may differ among individuals.
- A reliance on text-based features may overlook the potential impact of multimodal content, such as images and videos, which could provide additional context crucial to understanding mental health-related posts.

To overcome the identified limitations and advance mental health post-classification, several future research works could be pursued, such as:

- Expanding the range of datasets to include various online platforms and real-world environments can improve model generalizability and acceptability in broader contexts.
- Incorporating dynamics and continuously updating datasets to reflect emerging language trends, which would ensure that different ML models stay relevant in mental health discourse.
- Exploring more sophisticated natural language processing (NLP) techniques, such as sentiment analysis and emotion recognition, could provide deeper insights into the emotional context of mental health-related posts.
- Inclusion of multimodal data, such as image and video analysis, would provide a more comprehensive understanding of mental health posts by capturing non-textual cues.
- Collaboration with mental health professionals could refine data labelling processes and enhance model accuracy, ensuring that classification criteria are aligned with expert interpretations.

5. CONCLUSION

In this comparative analysis of six ML approaches for the classification of mental health-related posts from different online platforms, we have gained valuable insights into their individual classifier strengths and limitations. NB and RF classifiers demonstrated commendable performances, providing solid baseline models with simplicity and robustness, respectively. The proposed SVM model showed as the top performer, showcasing its ability to distinguish between different classes in the nuanced task of mental health post-classification, whilst XGBoost model also displayed strong classification capabilities, contributing to reliable predictive accuracy. The DT classifier faced challenges capturing the difficulties of mental health-related language, highlighting a trade-off between simplicity and predictive power, whilst LR proved highly effective, emphasizing its suitability for binary and multiclass classification tasks in this context. However, the choice of an ML model for mental health post-classification should be made with careful consideration of trade-offs between interpretability, simplicity, and predictive power. While SVM stands out as the top performer in this study. Future research may explore ensemble approaches and parameter tuning to refine model performances in this sensitive domain. These findings contribute to the growing body of knowledge in applying ML to mental health classification task, ultimately aiding in the development of more accurate and reliable tools for online mental health related content analysis.

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