Enhancing Suicide Detection via Chi-Square-Based Feature Selection and Machine Learning

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Abstract: Suicidal ideation detection has emerged as a crucial issue in mental health research, especially as social media use has increased and users are more likely to reveal psychological distress. In this study, an AI-driven approach to detecting suicide intent on Twitter is proposed using machine learning techniques. Natural Language Processing (NLP) techniques were used to collect and preprocess a dataset of tweets, from which features were selected using the SelectKBest algorithm, which is based on chi-square analysis. Using an 80:20 train-test split, four classification models—AdaBoost, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Decision Tree—were trained and evaluated. The SVM classifier achieved the highest accuracy of 89.66% and the highest precision of 91%, outperforming the other classifiers in detecting suicidal tendencies in social media posts. For the early detection of suicide risk, the results validate the effectiveness of conventional machine learning models when combined with appropriate feature selection techniques. This work shows how AI can be integrated into real-time mental health monitoring systems for early intervention and prevention.

1. Introduction

The increasing prevalence of suicidal thoughts in adults and children is a serious global public health concern. Because social media is so widely used, people frequently use it to share their emotional distress and psychological vulnerabilities, making it a useful tool for real-time mental health monitoring. [1], [8]. Artificial intelligence (AI) and machine learning (ML) techniques have shown promise in identifying patterns and behavioral indicators suggestive of suicidal intent by analyzing user-generated content on websites such as Reddit and Twitter. [3], [9], and [20].

Suicide-related posts have been identified and categorized by recent studies using advanced models, ranging from CNNs and BiLSTM to Naive Bayes and Support Vector Machines (SVM) [5, 14, 18]. One example is the ability of transformer-based models with explainable AI (XAI) features to predict suicidality in real-time among young people who use crisis text lines, as demonstrated by Julia Thomas et al. [1]. A multimodal approach that uses linguistic cues, behavioral signals, and metadata to achieve good classification accuracy for tweets about suicide was also presented by Chatterjee et al. [21], [22].

Additionally, social media's psychological effects have been examined in relation to problematic usage patterns, perfectionistic self-presentation, and the impact of targeted advertising. These factors have been connected to a decline in mental health and an elevated risk of suicide [2], [4]. This expanding body of research provides scalable and proactive treatments, highlighting the potential and need of AI-driven systems in suicide prevention [6, 7, 10].

The objective of this research is to develop a robust AI-enabled classification logic that can recognize information on Twitter that is pertinent to suicide by combining multi-feature analysis, natural language processing, and explainable machine learning in light of these developments. The proposed method seeks to enhance suicide ideation detection models' accuracy, interpretability, and real-time applicability to enable timely mental health interventions.

2. Related Work

Julia Thomas et al. [1] concluded that LSTM layers combined with transformer-based language models can accurately and consistently predict suicidal thoughts and behavior in youth using crisis text lines. Compared to traditional machine learning baselines, the model's accuracy of 0.79 and AUC of 0.89 were superior. The addition of SHAP-based explainability made the system interpretable for therapeutic use, which aided in decision-making and real-time mental health treatments. The results demonstrate that early suicide risk identification is possible with explainable AI solutions in digital mental health services.

Marie Leiner et al. [2] investigate the significant effects of social media advertising on kids' and teens' emotional and physical well-being. According to the authors, the widespread presence of targeted advertising on social media platforms has caused major disturbances in young people's sleep patterns, cognitive capacities, physical well-being, academic achievement, and interpersonal skills. They draw attention to the differences between the less regulated, highly focused tactics that are common in the digital sphere and conventional television marketing techniques. Constant internet connectivity is linked to increased rates of psychological discomfort, anxiety disorders, and suicidal tendencies in teenagers, according to the study. The authors urge responsible media usage, strong regulatory frameworks, and greater awareness in order to protect young people's wellbeing in the digital age.

Waleed Bin Tahir et al. [3] conducted a comprehensive review of machine learning and deep learning techniques for detecting depression through social media platforms. The study proposes a generic architecture and evaluates various ML/DL models applied to platforms like Twitter and Reddit. It also assesses datasets commonly used for depression detection tasks. The paper identifies key challenges and research gaps in the domain. This work serves as a foundation for developing robust mental health monitoring tools.

Sommerfeld et al. [4] investigated how perfectionistic self-presentation and problematic social media use mediate the relationship between attachment insecurities and depression in adolescent girls. Analyzing data from 100 participants aged 11.4–16.6 years, they found that both attachment anxiety and avoidance were linked to increased perfectionistic self-presentation, which subsequently led to higher problematic social media use and elevated depressive symptoms. These findings highlight the complex interplay between attachment styles, self-presentation behaviors, and social media use in contributing to adolescent depression.

Noviyanti P. et al. [5] aim to develop a machine learning model capable of analyzing the sentiments of tweets pertaining to suicidal thoughts. The researchers intend to use the Naive Bayes algorithm to find signs of suicidal intent on Twitter. By showcasing the ability of machine learning techniques to identify individuals at risk based on their social media activity, this approach supports early intervention strategies.

Femi Duyilemi et al. [6] look into the potential applications of artificial intelligence (AI) to prevent suicide among Inuit people in Canada's Nunavut territory. The suicide rate among Inuit is significantly higher than the national average, especially among young men. Artificial Intelligence (AI) technology may enhance mental health services in this remote region, according to Duyilemi's analysis of eight studies published between December 2014 and December 2024. He emphasizes the importance of actively involving stakeholders, identifying and minimizing ethical concerns, and consistently improving AI systems' accuracy. To effectively tackle the unique challenges faced by the Inuit community, the evaluation highlights the need for culturally aware AI applications.

Esteban A. et al. [7] investigate the viability of automated depression screening using social media data. The study's primary objective was to determine how frequently symptoms from the Beck Depression Inventory (BDI) appeared in social media posts. By looking at user-generated content, they aimed to determine how well online platforms detect and monitor these symptoms. The study found that certain BDI symptoms are more frequently and reliably present on social media, indicating that these platforms may be helpful tools for monitoring and early depression detection. However, the study does highlight the challenges of accurately assessing less frequently reported symptoms, indicating the need for better automated mental health assessment techniques.

Hesham Allam et al. [8] look into the use of artificial intelligence (AI) to detect suicidal thoughts on Twitter and other social media platforms. The researchers developed a machine learning model that scans tweets for patterns suggested by suicidal thoughts. The program uses natural language processing (NLP) and sentiment analysis to find emotional and textual markers linked to suicidal thoughts, increasing detection accuracy and reducing false positives. With 85% accuracy, 88% precision, and 83% recall, the study showed impressive predictive performance in identifying potential suicide posts. An AUC of 0.93 for precision-recall further demonstrated the model's potential for real-time mental health monitoring and intervention while also confirming its reliability. These findings show how machine learning can transform suicide prevention by offering a scalable and efficient way to deliver mental health services.

Bhuiyan et al. [9] explore the utilization of machine learning (ML), deep learning (DL), and natural language processing (NLP) techniques to detect suicidal ideation through social media analysis. The study emphasizes the critical need for effective strategies to identify and support individuals expressing suicidal thoughts online, leveraging technological innovations to enhance suicide prevention efforts. By analyzing vast amounts of unstructured social media data, the authors highlight how ML and DL models can identify linguistic patterns, keywords, phrases, tones, and contextual cues associated with suicidal ideation. The review also addresses the real-world effectiveness, limitations, and ethical considerations of employing these technologies, advocating for responsible development and usage to ensure they serve as life-saving tools without exacerbating existing inequities.

Burnap et al. [10] suggested a multi-class machine learning model to categorize suicide-related tweets into categories, such as suicidal thoughts messages, prevention messages, and seeking help messages. The work trained several classifiers, including Support Vector Machines and Random Forest, on annotated Twitter datasets with an F1-score of 0.84 for suicidal content. By both contextual and linguistic characteristics, the model could differentiate among varying levels of intent and concern. Their method sets a high value on the importance of correct classification in supporting suicide prevention efforts through social media surveillance. The research shows the capability of machine learning to identify individuals who are at risk across a range of emotional states.

Ji et al. [11] provide a comprehensive analysis of machine learning techniques for identifying suicidal thoughts (SID), with an emphasis on data sources such as online user content, surveys, suicide notes, and electronic medical records. Researchers differentiate between automated methods that use machine learning to analyze web data and clinical methods that involve expert interactions. Two examples of machine learning methods that the authors highlight as being advantageous and having uses in SID are deep learning and feature engineering. They address the shortcomings of existing approaches and provide new research directions to improve the precision and dependability of SID systems. In this review, the significance of machine learning in early suicide attempt detection and prevention is highlighted.

V. Patel et al. [12] suggested a hybrid feature-based method that uses textual, lexical, and semantic cues to identify activity related to suicide on Twitter. [12]. The study used emoticons, synonym-based traits, and unigram, bigram, and trigram features to improve classification accuracy. A number of machine learning models were assessed, such as Random Forest, SVM, and Naive Bayes. SVM showed exceptional predictive abilities by achieving the highest accuracy of 94.67 percent among these. By looking at social media, their method highlights the importance of hybrid traits in the early detection of suicidal thoughts.

Colombo et al. [13] carried out a thorough investigation into the communication preferences and connectivity of suicidal Twitter users. In order to comprehend the structural patterns and interactions among users expressing suicidal thoughts, the study used social network analysis techniques. They found that suicidal individuals are more likely to feel lonely, interact with people less frequently, and receive fewer responses—all of which may make them more vulnerable. The study emphasized how the dynamics of online communication may indicate mental health hazards, and that monitoring these trends should help efforts for early identification and intervention. The study emphasizes the significance of social structure in social media suicide prevention tactics.

Du et al. [14] formulated a deep learning model to detect mental stressors that can signal suicide risk in social media postings. Utilizing marked up Reddit posts and bidirectional LSTM models, the research autonomously detected stressors like relationship problems, anxiety, and depression. With outstanding recall and accuracy, their method drastically surpassed conventional techniques in classifying several categories of stressors. The findings indicate that deep learning is a powerful means of capturing environmental and semantic features associated with suicidal ideation. Through mining user-generated data from web sites, this study illustrates how AI may assist in early suicide prevention.

Varathan and Talib's [15] methodology for early identification of suicide relies on keyword extraction analysis of tweets and supervised machine learning. Based on content classification methods and filtering out tweets that included suicidally related terms, the algorithm was capable of differentiating between suicidal and non-suicidal tweets. Content filtering and natural language processing were used by them to identify mental health risks practically in real-time. The findings proved that it is possible to utilize Twitter as a monitoring tool to prevent suicide. This project was a pioneering effort to track public mental health by combining AI and social media.

Rabani et al. [16] suggested a system based on ensemble and machine learning to identify suicidal intent from tweets. User tweets were taken as the basis to extract behavioural and linguistic details using classifiers such as Random Forest, Decision Tree, and Support Vector Machine. Ensemble using these models aggregated to a degree of accuracy of 93.2% with better performance over the application of individual models. The research illustrates how suicide risk assessment can be made more accurate by employing hybrid methods. The research adds to the expanding body of AI-based mental health surveillance through its focus on model reliability and early intervention.

Aldhyani et al. [17] proposed a technique that combines deep learning and machine learning models to identify and evaluate suicidal ideation on social media. For text representation, they used word-embedding methods like TF-IDF and Word2Vec on publicly accessible Reddit datasets. To determine whether or not social media posts were suggestive of suicidal ideation, the study used a hybrid model that combined Convolutional Neural Networks (CNN) with Bidirectional Long Short-Term Memory (BiLSTM) and the XGBoost algorithm. With a 95 percent accuracy rate and a detection accuracy of 91 point five percent, the CNN-BiLSTM model outperformed the XGBoost model. These findings show how hybrid deep learning techniques may improve the detection of suicidal thoughts in social media posts.

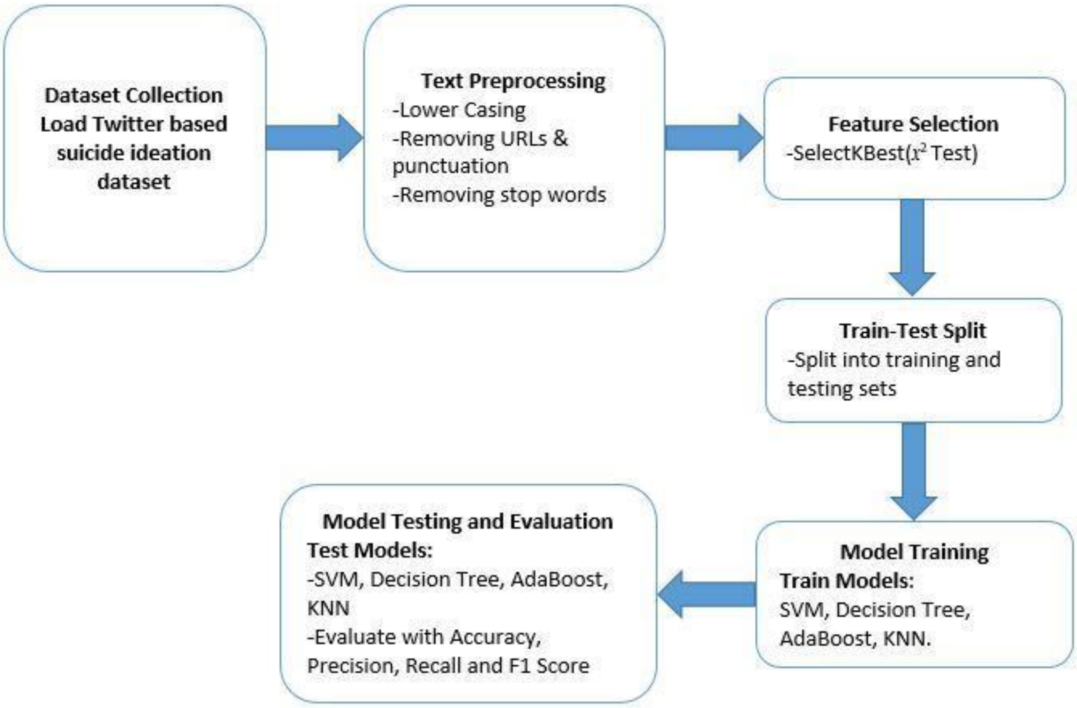
O'Dea et al.'s study, "Detecting Suicidality on Twitter,". [18] aimed to ascertain whether the content of tweets concerning suicide could be utilized to gauge the degree of anxiety that the tweeters were displaying. In a two-month period, 14,701 tweets about suicide were gathered by human coders, who categorized 14% as "strongly concerning," 56% as "possibly concerning," and 29% as "safe to ignore.". With $\kappa = 0.55$, the study's inter-rater agreement rate was 76%. Then, machine learning algorithms matched human classification accuracy by correctly classifying 80% of "strongly concerning" tweets. The ways in which people may express suicidality on Twitter are highlighted in this study, along with the use of automated techniques to swiftly identify and react to risky posts.

Kumar Piyush et al. Examine whether Twitter tweets can be used to spot depressive symptoms in users [19]. In order to identify symptoms of depression, the researchers used a variety of machine learning classifiers to extract linguistic and emotional information from tweets. According to their research, classifier performance is enhanced by combining these features; the Support Vector Machine achieved an accuracy of 89%. The importance of careful feature selection in enhancing depression detection models is illustrated by this study. The researchers think that expanding the model's emotional features and testing the strategy across several datasets could improve its efficacy even more.

Moumita Chatterjee [20] offers a thorough method for spotting suicidal ideas posted on social media. The researchers created a multimodal model that incorporates multiple feature groups to improve the detection of suicidal thoughts. The suggested approach, which used logistic regression, identified posts that were suggestive of suicidal thoughts with an accuracy of 87%. This study highlights the effective monitoring and management of mental health issues on social media through the integration of various data elements and machine learning techniques

3. Proposed Work

Step 1: Dataset Collection
Step 2: Text Preprocessing
Step 3: Feature Selection
Step 4: Train-Test Split
Step 5: Model Training
Step 6: Model Testing and Evaluation
Proposed system workflow



Step 1: Dataset Collection
In this step, suicidal ideation-related hashtags and phrases are used to gather Twitter data. Suicidal and non-suicidal categories are typically applied to the dataset. The accuracy of the model is determined by the variety and quality of the data, which forms the basis of the entire process.
Step 2: Text Preprocessing
The unformatted tweets are cleaned up. This entails converting the text to lowercase and eliminating special characters, stop words, punctuation, and URLs. In order to prepare the data for analysis, words can also be reduced to their most basic form using lemmatization, tokenization, or stemming.
Step 3: Feature Selection
Following preprocessing, the SelectKBest method with the Chi-square test is used to choose the most pertinent attributes. By removing unnecessary or redundant data, this step lowers dimensionality and enhances model performance. It guarantees that the classifier concentrates on characteristics that are most indicative of suicidal thoughts.
Step 4: Train-Test Split
After that, a typical 80/20 ratio is used to separate the dataset into training and testing sets. This makes it possible to train the model on a sizable portion of the data while validating it on the remaining data. Better generalization and an objective assessment of the model's performance are guaranteed by a well-structured split.
Step 5: Model Training
The training data is used to train a variety of machine learning algorithms, including K-Nearest Neighbors (KNN), Decision Trees, AdaBoost, and Support Vector Machines (SVM). Each algorithm searches the incoming data for patterns in order to classify tweets. Hyperparameters can be optimized by adjusting the model.
Step 6: Model Testing and Evaluation
The test data is used to assess the trained models. Metrics like F1-Score, Accuracy, Precision, and Recall are used to gauge performance. In this step, the best model for detecting suicidal ideation is identified, and its suitability for early detection is assessed.

4. Results and Discussions

Using data from Twitter, the efficacy of four machine learning models—SVM, KNN, Decision Tree, and AdaBoost—in detecting suicidal thoughts was assessed. With the best accuracy of 89%, precision of 91%, and F1-score of 89% among these models, the Support Vector Machine (SVM) model was

determined to be the most dependable method for separating suicidal tweets from non-suicidal ones with the fewest false positives.
As a competitive substitute for SVM, the Decision Tree model also performed well, achieving an accuracy of 88% and an F1-score of 88%. Although slightly less accurate than SVM, it strikes a reasonable balance between recall and precision. But the K-Nearest Neighbors (KNN) model performed the worst, with an accuracy of only 72.63% and a comparatively low F1-score of 64%. This implies that KNN is less successful for this classification task because it has trouble handling the high-dimensional and potentially sparse nature of text input.
AdaBoost obtained a moderate F1-score of 80 % and an accuracy of 82.40 %. Although it outperforms KNN, it may not be as efficient as SVM or Decision Trees due to its sensitivity to outliers or noisy data.
The analysis shows that the SVM model is the best at identifying suicidal thoughts in this study, with the Decision Tree model coming in second. For this particular NLP-based task, KNN is not a suitable fit.

Table 1. Proposed system Result Comparison

Model	Accuracy	precision	Recall	F1-Score
SVM	89.66%	91.00%	88.00%	89.00%
KNN	72.63%	83.00%	65.00%	64.00%
Decision Tree	88.83%	89.00%	87.00%	88.00%
AdaBoost	82.40%	87.00%	78.00%	80.00%

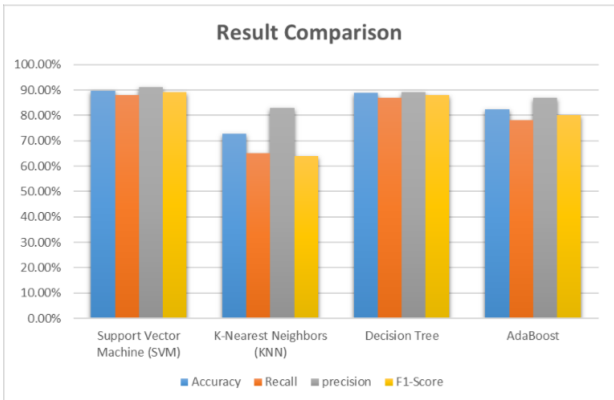


Figure 2. Proposed system Result Comparison

5. Conclusions and Future work

According to evaluation results, the Support Vector Machine (SVM) performed better overall than the other four machine learning models (KNN, AdaBoost, Decision Tree, and SVM) when it came to detecting suicidal ideation using Twitter data. SVM achieved the best accuracy (89.66%), precision (91.00%), and F1-Score (89.00%) for classifying suicidal tweets with low false positives and false negatives.
The Decision Tree model performed competitively with an accuracy of 88.83% and a balanced precision-recall score, making it a good alternative. But in this classification test, K-Nearest Neighbors (KNN) was ineffective, trailing behind with an accuracy of only 72.63% and the lowest F1-Score and recall. Although AdaBoost performed fairly well, its consistency could not match that of SVM or Decision Trees.
The study concludes that SVM is the most dependable and successful model for identifying suicidal thoughts in Twitter data, and it is recommended for future use or real-world applications.
Building on the encouraging outcomes of the Support Vector Machine (SVM) model, future research could concentrate on different strategies to improve the system's functionality and performance. First, compared to conventional machine learning models, using deep learning techniques like LSTM, BERT, or transformers may better capture sentimental patterns and contextual nuances in tweets. By increasing the dataset's size and diversity, including data from various regions and multilingual tweets, the model's generalizability and robustness can be enhanced.

Furthermore, combining topic modeling and sentiment analysis may offer additional understanding of users' emotional states. Early intervention efforts could be improved by putting in place a real-time monitoring system that highlights high-risk content and notifies mental health specialists. Finally, using explainable AI (XAI) techniques will aid in the interpretation of model decisions, guaranteeing ethical and transparent use in delicate applications such as the detection of suicidal thoughts.
Author Statements:

- Ethical approval: The conducted research is not related to either human or animal use.
- Conflict of interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
- Acknowledgement: The authors declare that they have nobody or no-company to acknowledge.
- Author contributions: The authors declare that they have equal right on this paper.
- Funding information: The authors declare that there is no funding to be acknowledged.
- Data availability statement: The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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