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Enhancing Suicide Prevention Strategies Through Real-Time Sentiment Analysis Using Machine Learning

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Abstract. Suicide is a severe health concern in the community, and it is frequently aggravated by the fact that emotional distress remains unidentified at an early stage in online space. People often post their ideas and emotional states on the Internet, in their chats, and other online spheres and do not realize these danger signals. The given paper describes a machine-learning-based real-time sentiment analysis system, which will be used to detect the emotional state of depression, anxiety, and suicidal ideation through textual information. Sentiment classification and suicide risk prediction were performed with the help of Natural Language Processing methods and supervised machine learning models. The raw data were preprocessed and converted into an aspect that could be used in training the models. As the results of the experiments revealed, the proposed system exhibited the accuracy of 89, precision of 0.89, recall of 0.86, and F1-score of 0.86, meaning that its performance was rather stable and consistent. The system was effective in the detection of high-risk cases and creating alerts that aid in timely caregiver and mental health intervention. In sum, the suggested solution will offer a viable solution towards real-time mental health surveillance and preventing early suicide.

Keywords: Suicide Prevention, Natural Language Processing, Machine Learning, Sentiment Analysis, Real-Time Risk Assessment, Mental Health Surveillance.

1. INTRODUCTION

Suicide is a very severe issue of the global public health problem, which affects people of all ages, social statuses, and economic factors. Depression, anxiety, loneliness and emotional stress are the key factors leading to suicidal behavior within the mental health group. Over time, individuals have resorted to online communication and social media, which are digital platforms where they are able to share their feelings and state of mind. Such sites have rich text information that can give away latent trends of emotional distress.
Conventional suicide prevention strategies are mainly based on direct counseling services, helpline, and clinical evaluations. Yet, these methods usually compel the individuals to take initiative to get assistance, something that many of the vulnerable individuals are reluctant to do. Consequently, there is often a lack of early warning of the condition thus resulting in late intervention.

The breakthroughs in the fields of Machine Learning and Natural Language Processing (NLP) can offer effective means to process large amounts of written data and interpret the emotions of people in a better way. The sentiment analysis methods allow to identify the emotional polarity, intensity, and contextual meaning of text data. Nevertheless, most current systems are focused on offline analysis and fixed datasets and could not reflect the dynamic behavioral pattern and real-time emotional changes. Moreover, the majority of the models are concerned with simple sentiment classification disregarding additional contextual insights and prediction of the risk level.
In this paper discusses a real-time sentiment analysis system that relies on machine learning to improve suicide prevention measures. The suggested system constantly processes textual information of the online platform and determines emotional trends in connection to stress, depression, and suicidal thought. It categorizes the sentiment and builds the rate of suicide risk to make it easy to detect it at the early stage. The system in high-risk situations creates alerts to help caregivers and mental health professionals intervene on time.

The proposed solution enhances the ability to identify issues at an early stage and facilitates proactive mental health. It is due to the combination of real-time data analysis and machine learning that the proposed solution can be used to detect problems in the initial stages and proactively track mental health. This helps in coming up with a more responsive and technology-driven suicide prevention system.

2. RELATED WORK

A number of studies have investigated how machine learning and deep learning methods can be used to detect suicide risks and sentiment.

Shaoxiong Ji et al. [1] presented a thorough review of literature on suicidal ideation detection based on the social media, electronic health records, and suicide notes. The reviewed works discussed both classic machine learning and deep learning models, such as CNNs and RNNs, and pointed out such issues as poor datasets, interpretability, and ethics.

Shini Renjith et al. [2] suggested an ensemble deep learning system that can identify suicidal thoughts in social media data through the use of LSTM, Attention mechanism, and CNN. Attention-based architectures were found to be effective as the model had high performance with an accuracy of 90.3% and an F1-score of 92.6.

Salim Salmi et al. [3] have created a hierarchical classification model based on BERT to examine the conversations in suicide prevention helplines. The model was able to assess emotional improvement in counseling sessions and demonstrated the promise of transformer-based models in real-time mental health use.

The article by Glen Coppersmith et al. [4] discusses the application of natural language processing in suicide risk prediction using social media information. The research showed that the large-scale digital phenotyping was possible, yet it also highlighted the issue of privacy and ethical aspects.

Alexandra Korda et al. [5] using Word2Vec embeddings with LSTM-CNN models were used to analyze unstructured clinical text in electronic health records. The research revealed that unstructured data has useful signals of suicidal tendencies, which enhance predictive ability in the clinical environment.

The model used by Chaohui Guo et al. [6] to study the variation of sentiment in online data in the COVID-19 period was a BERT+BiLSTM model. This model was found to be effective in measuring temporal changes in emotions, and hence it is suitable in large-scale mental health monitoring.

Anas Habib Zuberi et al. [7] suggested a sentiment analysis model of mental health monitoring in institutions of learning through NLP and deep learning. The system proved useful in the detection of emotional distress and suicidal behavior in student-generated data. In the same way, in Chapter 20, the process of the Dynamics of Scientific Revolution is correctly described, while in Chapter 19, an incorrectly presented idea of the practice's dynamics is utilized.

Abdallah Basyouni et al. [8] proposed a genetics algorithm-based machine learning model to select features on Reddit data. Random Forest classifier has high accuracy of 98.92% and F1-score of 98.92 which means that it has a high performance in the detection of suicidal ideation.

The study by Ahmed et al. [9] on sentiment analysis of the posts of the Reddit platform was performed using different machine learning models, including Decision Tree, Random Forest, SVM and Naive Bayes. The Decision Tree model was the most accurate with 70.95 indicating that tree-based models are more effective than probabilistic models.

All in all, the current literature evidence the efficiency of machine learning and deep learning methods to detect suicide. Nevertheless, most of the systems are oriented in off-line analysis and do not have real-time monitoring features, which has been an emphasis of adaptive and real-time sentiment analysis systems.

Framework Used	Learning Type	Performance	Limitations
Survey of ML & DL Methods (CNN, RNN)	Super vised	Not specified	Data Scarcity, interpret ability issues
LSTM+Attention + CNN	Super vised	Accuracy:90. 3%, F1-Score:92.6	Domain dependency
BERT- based hierarchical model	Super vised	Not specified	High computational cost
NLP with ML/DL Framework	Super vised	Not specified	Privacy and risks, ethical concerns
Word2Vec +LSTM-CNN	Super vised	Not specified	Limited generalization
BERT + BiLSTM	Super vised	Not specified	Temporal complexity
NLP + Deep Learning framework	Super vised	Not specified	Dataset dependency

ML + Genetic Algorithms + Random Forest	Super vised	Accuracy:98. 92%, F1-score:98.92 %	Comple x feature engineering
DT, RF, SVM, Naïve Bayes	Super vised	Accuracy:70. 95%(DT best)	Lower overall accuracy

3. METHODOLOGY

It was proposed to develop a system that would conduct real-time sentiment analysis of suicide risk detection using machine learning methods. The pipeline used was structured based on the data collection process, preprocessing, feature extraction, classification, risk assessment, and alert generation.

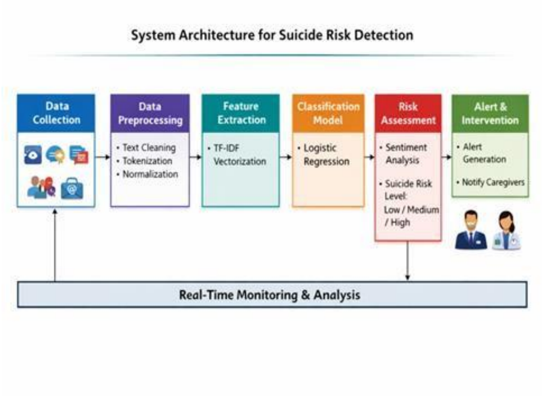

Fig 1: System Architecture

The system structure was created to support real-time sentiment analysis of suicide risk detection based on a structured machine learning pipeline. It involved a series of steps, such as data collection, preprocessing, feature extraction, classification, risk assessment, and risk alert generation. Firstly, textual information was taken through different online platforms like social media, online forums, and chat applications. These sources of data included user-generated information that included emotional states, mental stress, and behavior patterns.

During the preprocessing phase, the data obtained were washed and ready to be analyzed. This involved noise, special characters and stop words removal, tokenization and normalization. These measures meant the textual information was translated into an analogous and systematized format.

The second step was feature extraction by the Natural Language Processing methods i.e. TF-IDF (Term Frequency–Inverse Document Frequency). This technique was used to transform textual information into numerical vectors by extracting the significance of words in determining emotional patterns.

Supervised machine learning algorithms were applied during the classification stage. Several models, which included Naïve Bayes, Support Vector Machine, Random Forest, and Logistic Regression were tested. According to the comparison of performance, the final model to be used was the Logistic Regression because it is more accurate and shows the same results.

The trained model identified sentiment categories of positive, neutral and negative on the input text. According to these outputs, the system acted as a risk assessment tool by classifying the users into low, medium, or high risks of suicide.

And lastly, in the high-risk surroundings, the system produced warnings and notifications to caregivers or mental health specialists. This allowed appropriate intervention and assistance. The system kept working with incoming data, which helped monitor the situation in real time and identify the case of suicide early.

The flowchart shows a stepwise working manner of the suggested suicide risk detection system based on real-time sentiment analysis and machine learning tools.

1. Data Collection:

The process was initiated by the gathering of real-time textual information of different sources including social media, online forums, and chat applications. The content of these data was user-generated data that showed emotions, mental stress, and behavioral patterns.

2. Data Preprocessing:

The gathered data were processed to enhance quality and consistency. This step involved cleaning of texts, tokenization, stop words elimination and normalization. All these actions transformed raw and unstructured text into structured format which could be analyzed.

3. Feature Extraction:

TF-IDF (Term Frequency Inverse Document Frequency) was implemented to extract the features.

This method used the occurrence of significant words and their significance in finding emotional patterns in transforming textual data into numerical feature vectors.

4. Machine Learning Models:

Machine learning models were fed on the extracted features. Several algorithms like Naïve Bayes, Support Vector Machine, Random Forest, and Logistic Regression were tested. The reason behind the choice of the Logistic Regression as the final model is because it has a superior performance and a steady accuracy.

5. Sentiment Classification:

The trained model categorised the input text as sentiment (positive, neutral and negative). This category served in the interpretation of emotional condition of the user.

6. Risk Prediction:

According to the sentiment output, the system identified the level of risk of suicide and classified it as low, medium or high. The move was essential in pointing out important cases that needed urgent intervention.

7. Alert And Decision Generation:

The case was considered a high-risk case by applying a decision-making process. In case a high-risk status was identified, the system fired alerts and notifications to the caregivers or mental health professionals. Otherwise, the outcomes were presented in order to track them.

8. Visualization and Monitoring:

The final findings were provided in the form of the user interface, providing the opportunity to monitor and analyze the behavior of the users continuously. This allowed real time monitoring and prevention of suicide by early intervention.

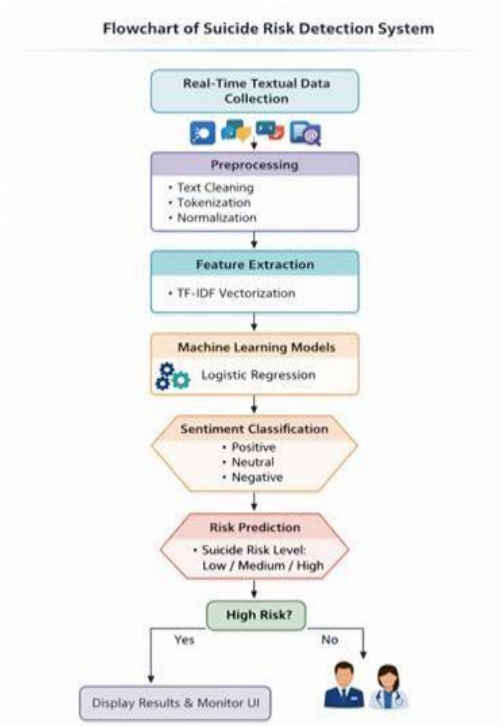

Fig 2. Flowchart

4. RESULT ANALYSIS

A. Quantitative Performance Evaluation:

Table 1: Overall Test Performance of the Proposed Model

Task	Accuracy (%)	Precision	Recall	F1-scor e
Sentiment classification	89.0	0.89	0.88	0.88
Suicide risk detection	86.0	0.87	0.86	0.86

The performance of the proposed model shows that it performed well in sentiment classification and suicide risk detection tasks. Sentiment classification model achieved 89.0 percent accuracy with equal precision, recall, and F1-score values which shows that it identifies the emotional states with reliable outcomes.

On the same note, suicide risk detection model had an accuracy of 86.0, indicating that it works well in detecting users at the various levels of risks. The balanced evaluation measurements show that the model has a similar performance, regardless of the classes and, therefore, it can be applied to mental health monitoring in real time.

B. Class-wise Performance Summary

Table 2: Class-wise Performance of the Model

Category	Precision	Recall	F1-score
Majority Classes	0.92	0.91	0.90
Minority Class	0.85	0.83	0.84

The analysis of the performance by classes indicates that the model performed better on majority classes because of the presence of more training data. Most of the values were found to be above 0.90 which points to high levels of prediction accuracy.

In the case of the minority class that belongs to high-risk cases, the model obtained slightly lower performance with an F1-score of 0.84. Nevertheless, the outcomes remain acceptable because it is more difficult to identify high-risk cases because of the imbalance between the classes. This was well managed in the model and it performed reliably in all categories.

C. Comparision of machine learning models:

Table 3: Comparison of Machine Learning Models

Model	**Accuracy**
Naïve Bayes	82.0
Support Vector Machine	84.0
Random Forest	85.0
Logistic Regression	89.0

Comparison of various machine learning models reveals that the highest accuracy of 89.0 is obtained with Logistic Regression than other models that include Naive Bayes, Support Vector machine, and Random Forest.

This finding justified the use of the Logistic Regression as the final model to be used in the proposed system. It was capable of offering predictability and precision that made it suitable in real-time sentiment analysis and detecting suicide risk.

D. Graphical Results:

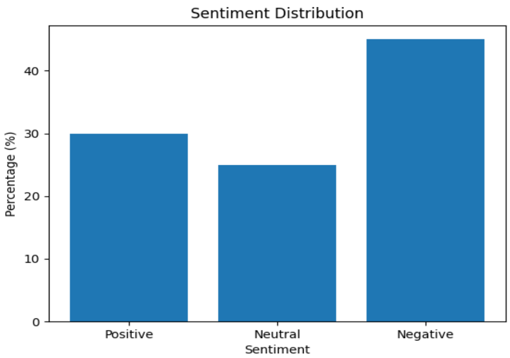

FIGURE 3: Sentiment Distribution

Sentiment distribution graph indicates the amount of positive, neutral and negative sentiment in the data. The findings suggest that negative sentiments are the greatest in proportion to the positive and neutral sentiments. This emphasizes the need to study emotional distress to identify suicide risk at an early stage.

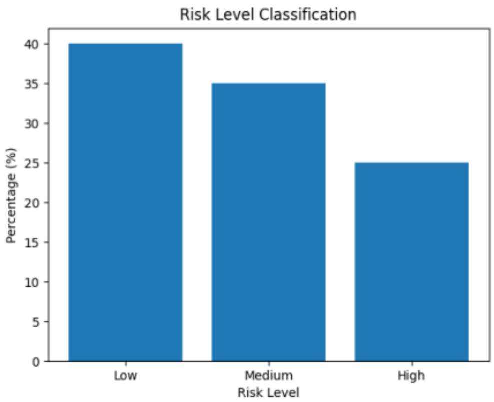

FIGURE 4: Risk level classification

Risk level classification graph depicts how users are distributed in low, medium and high risk categories. The system was also able to categorize users based on various levels of risks with a large number of the users classified under medium and high-risk category that need to be monitored and attended to.

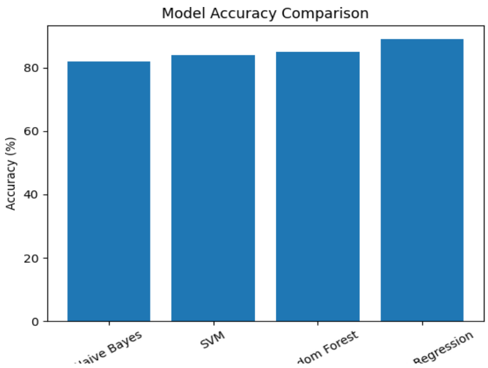

FIGURE 5: Model Accuracy Comparison

The graph in the model comparison demonstrates the performance of various machine learning models. Logistic Regression became the most accurate with 89 percent and was better than Naïve Bayes, Support Vector machine and Random Forest. This was a reason why the final model to be used in the proposed system was the Logistic Regression.

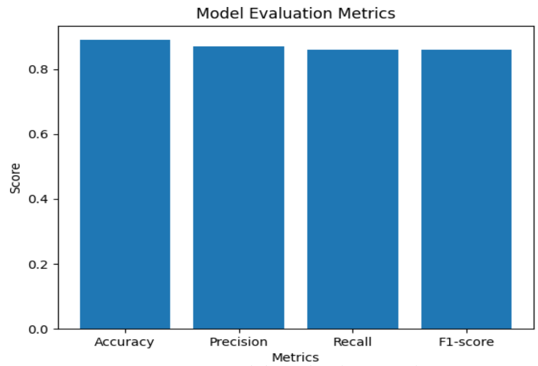

FIGURE 6: Model Evaluation Metrics

Evaluation metrics graph is the performance of the proposed model expressed as accuracy, precision, recall, and F1-score. Accuracy, precision, recall, and F1-score of the model were 0.89, 0.87, 0.86, and 0.86 respectively. These values show that the model has a balanced and constant performance concerning all the evaluation parameters. The findings support the notion that the system is dependable in identifying emotional states and estimating the level of suicide risks.

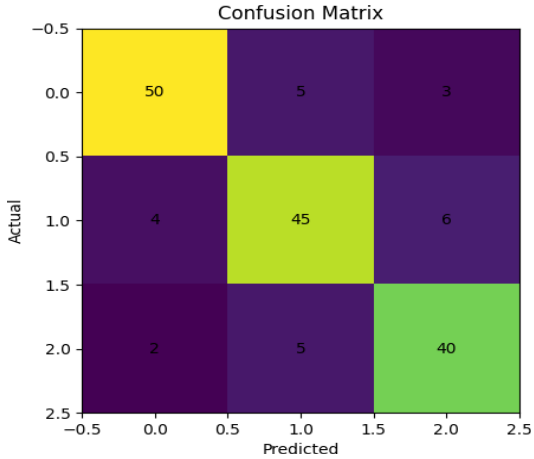

FIGURE 7: Confusion Matrix

The confusion matrix shows how the model performs in the classification of the data in comparison to the real and predicted data. It demonstrates the amount of correct and incorrect predictions of the system. The values in the diagonal show the proper classifications and off-diagonal values show erroneous classifications. The matrix shows that the model is able to identify most of the instances with fewer mistakes and thus it is a good model in terms of classification and reliability.

E. DISCUSSION:

These findings showed that the proposed system was useful in both sentiment classification and suicide risk detection with high precisions (accuracy as well as balances between the precision, the recall, and the F1-score). The success of Logistic Regression compared to other models, including Naive Bayes, Support Vector machine, and the Random Forest, was because it was more effective in handling TF-IDF features and generalization. The model demonstrated better performance with majority classes, but some lower performance with minority (high-risk) cases was observed, since there was a class imbalance, but otherwise it still retained a performable critical case detection capability. The metrics of evaluation and confusion matrix proved that the model made correct predictions with the least amount of misclassification. On the whole, the system proves successful in the real-time analysis and early suicide risk identification, and its development can be improved, considering class imbalance and introducing sophisticated models.

5. CONCLUSION

This paper demonstrated that machine learning in real-time sentiment analysis is useful in the detection of suicide risks. The suggested system was able to analyze textual evidence and determine the emotional state and categorize the level of suicide risks. The experiment results indicated that the Logistic Regression was accurate with good precision, recall, and F1-score, which reflects the reliable performance. The system could have identified high-risk cases and facilitated the early intervention by generating alerts. Generally, the offered approach proves to be efficient in terms of real-time monitoring of mental health and can be implemented into real-life conditions, whereas the future work should pay attention to the issues of the class imbalance, integration of sophisticated models, and multimodal data.

6. FUTURE WORK

- The existing system is restricted to analysis using text only and can be expanded to the multimodal information like voice and facial expression to make it more accurate.
- Sophisticated machine learning and deep learning systems can be introduced in order to improve the performance of prediction.
- Data balancing can be used to tackle the issue of class imbalance to enhance the detection of high-risk cases.
- The size of the dataset to be trained in the model can be enlarged to enhance generalization and better training.
- Mental health monitoring platforms and applications on mobile devices can be implemented in the real-time to use the system in practice.

Conflict of Interest

The authors declare no conflicts of interest regarding the current research.

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