Suicide Detection System Using Web Tracking

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ABSTRACT

Detection of suicide risk is a highly prioritized, yet complicated task. A total of 1,64,033 suicides were reported in India in the year 2021. With the high rate of people dying from suicide, the speed of information disseminated through the Internet should be an advantage to make good use of it to detect the signs of suicide in a faster way. Suicide detection system aims to detect suicide in a timely manner by tracking browsing data. The suicide and Depression Detection dataset used in this system along with a Chrome extension will help determine the risk of suicide. This system can be used by Parents, Schools, and Colleges to help prevent people from committing suicide.

Keyword : - *NLP, Suicide detection system, Web tracking, Early detection, Real-time monitoring, Support systems, Accurate identification, Machine learning, LSTM (Long Short-Term Memory), Sequential data.*

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1. Introduction

Natural Language Processing (NLP) is a subfield of artificial intelligence and computational linguistics that focuses on enabling computers to understand and process human language. NLP seeks to bridge the gap between human communication and computer understanding, by enabling computers to analyze and understand the complexities of human language in a way that is meaningful and useful. NLP is used to detect the texts present in the websites visited and identify websites that could induce thoughts of depression and suicide.

2. Literature Survey

A. The Automatic Classification of Suicidal and Non-Suicidal.

The paper explores the use of natural language processing to predict the likelihood of a musician's suicide. It builds a corpus of songs and calculates vocabulary and syntactic features to create a suicide/non-suicide song classifier. It is able to achieve up to a 70.6% classification rate with the Simple Cart algorithm, a 12.8% increase over the majority-class baseline. This suggests that syntactic and vocabulary features are useful indicators of the likelihood of a lyricist's suicide.

B. Review of natural language processing in the Identification of suicidal behavior

NLP approaches offer powerful tools for identifying psychological conditions, but their accuracy in discerning suicidal thoughts or behaviors is unknown. Results suggest strong performance, but limitations include non-standardized reports, small sample sizes, and biased test construction samples. Future work is needed to understand their dissemination and implementation.

C. A Transformer-Based Approach To Detect Suicidal Ideation Using Pre-Trained Language Models.

In 2020, a study by Farsheed Haque, Ragib Un Nur, Shaeekh Al Jahan, Zarar Mahmud, and Faisal Muhammad Shah proposed a new detection approach using Transformer models in the language domain. The study analyzed raw social media posts to classify suicidal ideation indications. Transformer models, including BERT, ALBERT, Roberta, and XLNET, performed better than conventional Deep Learning architectures like Bi-LSTM.

D. A machine learning approach predicts future risk of suicidal ideation from social media data.

Arunima Roy, Katerina Nikolitch, Rachel McGinn, Safiya Jinnah, William Klement, and Zachary A. Kaminsky

In 2020 study by Roy et al. developed an algorithm called "Suicide Artificial Intelligence Prediction Heuristic (SAIPH)" to predict future suicidal thoughts based on Twitter data. The algorithm was trained on psychological constructs related to suicide. The study found significant associations between algorithm SI scores and county-wide suicide death rates, particularly in younger individuals.

***E.* Machine Learning for suicidal ideation identification: A systematic literature review.**

In 2022 Wesllei Felipe Heckler, Juliano Varella de Carvalho, Jorge Luis Victória Barbosa worked on Suicidal ideation as the first stage in the risk scale, being a potential gate for suicide prevention. 7 Machine learning emerged as a promising tool for helping in preventing suicide through the identification of individuals at risk. Therefore, this paper presents how machine learning can help in suicidal ideation identification. The author proposed a taxonomy of machine learning techniques explored in this area and a taxonomy for highlighting the current research challenges. In a general way, studies explored data from social media and performed a text analysis to investigate suicidal tendencies in the individuals' language. Moreover, deep learning models seem to be a tendency in this area nowadays. Future studies in suicidal ideation should investigate generic and proactive models that do not depend on users' self-reports.

F. Detection of Suicide Ideation in Social Media Forums Using Deep Learning.

A study by Tadesse, Lin, Xu, and Yang in 2019 aimed to detect suicide ideation on social media using deep learning and machine learning-based classification approaches. They applied an LSTM-CNN combined model to Reddit social media. The study found that the combined neural network architecture with word embedding techniques achieved the best relevance classification results. The results also supported the strength and ability of deep learning architectures to build effective models for suicide risk assessment in various text classification tasks. This research highlights the importance of early detection and recognition of suicidal posts on social media.

***G.* Application of Natural Language Processing (NLP) in Detecting and Preventing Suicide Ideation.**

Abayomi Arowosegbe, Tope Oyelade, and Paul B. Tchounwou conducted a 2023 study on the potential of machine learning and artificial intelligence (NLP) in detecting, diagnosing, and treating suicide. They searched various databases for studies on NLP in suicide ideation or self-harm, generating 387 results. The review found that NLP could provide low-cost and effective alternatives to resource-intensive methods of suicide prevention, thereby guiding risk prediction and advancing suicide prevention frameworks.

H. A Comparative Analysis of Suicidal Ideation Detection Using NLP, Machine, and Deep Learning

This study focuses on detecting suicidal ideation through online social network analysis on Twitter. Researchers applied text pre-processing and feature extraction techniques to train machine learning and deep learning models. Experiments were conducted on 49,178 instances retrieved from live tweets by 18 suicidal and non-suicidal keywords using Python Twitpic API. The results showed that the RF model achieved the highest classification score among machine learning algorithms, with an accuracy of 93% and an F1 score of 0.92.

***I.* Exploring the Suicide Mechanism Path of High-Suicide-Risk Adolescents—Based on Weibo Text Analysis**

The study explored the relationship between psychological pain, hopelessness, and suicide stages of high-suicide-risk adolescents. Qualitative analysis showed that 36.2% of high-suicide-risk adolescents suffered from mental illness, and hopelessness was significantly negatively correlated with suicide stages.

3. Methodology

Users who opt to participate in the suicide detection system will initiate the process by installing a browser extension, ensuring full consent and voluntary engagement.

The browser extension is designed to collect the user's web surfing history, encompassing timestamps, page titles, visited URLs, and other relevant metadata, all gathered with explicit permission from the user.

Once collected, the extension securely transmits this data to a Flask backend server, which serves as an intermediary for handling and processing the incoming information.

The Flask backend incorporates a sophisticated web content scraper module. This component, tasked with processing the received data, systematically traverses the URLs extracted from the browser history, extracting pertinent content including text and images.

Subsequently, the scraped web content is passed through a dedicated classifier. The primary objective of this classifier is to meticulously analyze the material for any indicators of self-harm, suicidal ideation, or related concerns. Leveraging state-of-the-art machine learning algorithms and natural language processing (NLP) techniques, the classifier scrutinizes the textual content, identifying relevant words, phrases, and sentiments indicative of potential mental health issues.

Upon analysis, the classifier assigns a score or label to the content, reflecting the severity or urgency of the identified concerns. This classification can range from binary (suicidal or non-suicidal) to nuanced gradations such as low, medium, and high risk.

Based on the classification results, the system can initiate various actions tailored to the severity of the identified issues. For instance, if the content is flagged as extremely concerning, designated mental health professionals, crisis hotlines, or specified contacts may receive an immediate alert, facilitating timely intervention and support.

Furthermore, users who voluntarily participate in the system are presented with supportive messaging encouraging them to seek assistance or explore available mental health resources. This proactive approach ensures that individuals navigating distressing online content are empowered to access appropriate support and care, fostering a compassionate and responsive digital environment.

Additionally, the system may integrate features such as anonymized data analysis to identify broader trends and patterns, contributing to ongoing research and the development of more effective suicide prevention strategies. By combining cutting-edge technology with ethical data practices and user-centered design, the suicide detection system endeavors to proactively address mental health challenges within the digital landscape, promoting safety, support, and well-being for all users.

3.1 System Architecture

Below is the diagram for text summarization process.

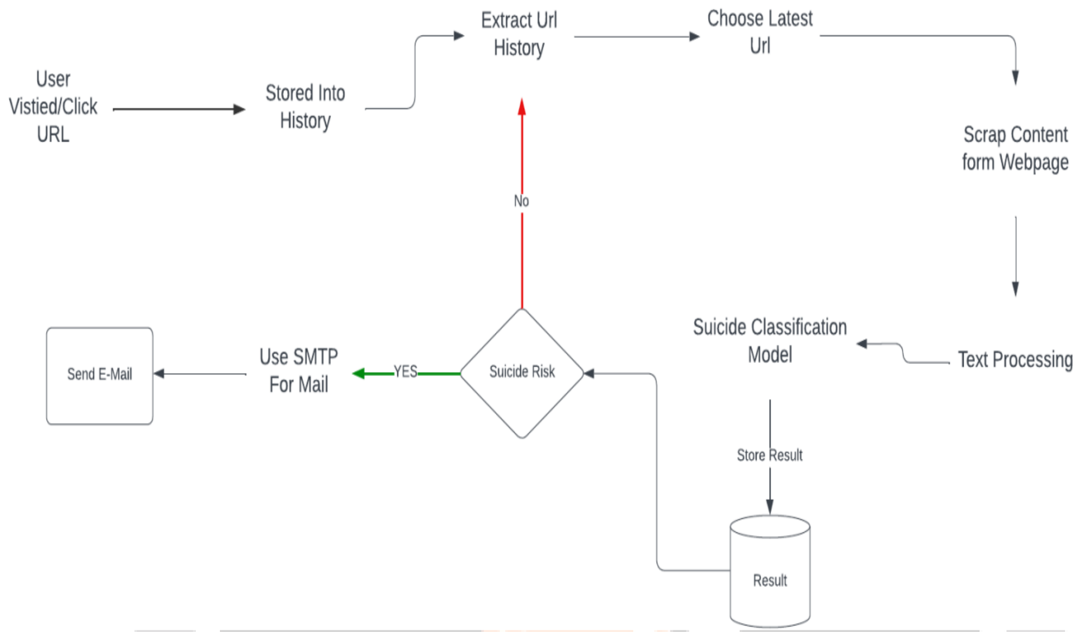


Fig 1. Activity Diagram

1. Sentiment Analysis

In recent years, research in suicide detection systems has witnessed a significant paradigm shift towards leveraging advanced natural language processing (NLP) techniques, particularly sentiment analysis, for early risk assessment. Traditional approaches primarily relied on static feature extraction methods, such as bag-of-words and n-grams, which often struggled to capture nuanced linguistic cues indicative of emotional distress or suicidal ideation. However, with the advent of deep learning architectures like Long Short-Term Memory (LSTM) networks, there has been a notable advancement in the ability to model temporal dependencies and contextual information present in textual data extracted from users' web history. These advancements have paved the way for more sophisticated suicide detection systems capable of analyzing sequential patterns and identifying subtle linguistic nuances associated with suicidal tendencies. Moreover, the integration of LSTM with word embedding techniques such as Word2Vec has enabled the creation of dense vector representations that capture semantic relationships between words, facilitating more accurate sentiment analysis and risk assessment. While early studies demonstrated promising results, the field continues to evolve rapidly, with ongoing efforts focused on optimizing model architectures, exploring multimodal data sources, and addressing ethical considerations surrounding privacy and data security in suicide risk prediction. Thus, understanding the evolution of sentiment analysis techniques within the context of suicide detection systems provides valuable insights into the current state-of-the-art and guides future research endeavors aimed at enhancing the effectiveness and reliability of suicide risk assessment algorithms.

2. Sentiment Analysis Techniques

Sentiment analysis encompasses various approaches, each tailored to analyze different aspects of textual data. Let us refer to some of the techniques used in Sentiment Analysis.

2.1 Document-Level Sentiment Analysis

The document-level Sentiment Analysis module analyzes a piece of text and determines whether the text has a positive or negative sentiment.

2.1.1 Bag-of-Words(BOW)

Bag-of-Words represents text as a collection of unique words, disregarding grammar and word order. BoW models are often combined with statistical methods or machine learning algorithms for sentiment classification. While BoW lacks sequential context, it serves as a baseline for sentiment analysis tasks.

2.1.2 Term Frequency-Inverse Document Frequency (TF-IDF)

TF-IDF calculates the importance of words in a document relative to a corpus. It assigns higher weights to words that are more frequent in the document but less frequent across the corpus, thus highlighting significant terms that may indicate sentiment.

2.1.3 Long short-term memory (LSTM)

LSTM networks are adept at modeling sequential dependencies in text data. While traditionally used for sequential tasks like language modeling and time series prediction, LSTM can be applied to document-level sentiment analysis by considering the order of words and sentences. LSTM's ability to capture long-term dependencies makes it effective in understanding the context and sentiment flow within documents.

2.2 Sentence-Level Sentiment Analysis

The sentence-level sentiment classification uses sentences as the basic unit and extracts words such as adjectives and nouns, which express a particular polarity.

2.2.1 N-gram Models

Bag-of-Words represents text as a collection of unique words, disregarding grammar and word order. BoW models are often combined with statistical methods or machine learning algorithms for sentiment classification. While BoW lacks sequential context, it serves as a baseline for sentiment analysis tasks.

2.2.2 Recursive Neural Networks (RNNs)

RNNs, including LSTM, excel at processing sequential data. In sentence-level sentiment analysis, LSTM networks process sentences word by word, capturing dependencies between words and inferring sentiment based on the overall context. LSTM's ability to retain information over long sequences makes it suitable for analyzing sentiment in sentences of varying lengths.

2.2.3 Convolutional Neural Networks (CNNs)

CNNs can also be applied to sentence-level sentiment analysis by treating text as one-dimensional sequences. CNNs use convolutional layers to extract features from input sentences, followed by pooling layers to aggregate information and make predictions. While CNNs are traditionally used for image processing, they have been adapted to text analysis tasks with success.

2.3 Aspect-Based Sentiment Analysis

The sentence-level sentiment classification uses sentence as the basic unit and extracts words such as adjectives and nouns, which expresses a particular polarity. A text analysis technique that divides the text data and defines its sentiment based on its aspects. It analyzes consumer feedback data by correlating emotions to different aspects of a product or service.

2.3.1 Aspect-Based Models

These models focus on identifying sentiment towards specific aspects or entities mentioned in text. Techniques such as attention mechanisms or memory networks enhance LSTM architectures to attend to relevant aspects within sentences or documents. By selectively focusing on salient aspects, these models provide nuanced sentiment analysis, capturing the sentiment expressed towards different entities or aspects.

2.3.2 Target-Dependent Sentiment Analysis

This approach involves identifying sentiment towards specific targets or entities mentioned in the text. LSTM networks augmented with target-specific attention mechanisms selectively attend to sentiment expressions related to particular entities, enhancing sentiment analysis precision. Target-dependent sentiment analysis enables fine-grained sentiment assessment by considering the sentiment expressed toward different targets within the text.

2..4 Fine-Grained Sentiment Analysis

The term is often used as a synonym for aspect-based sentiment analysis, multiclass polarity classification, or subsentence-level sentiment analysis — as opposed to coarse-grained opinion mining performed at document and sentence levels.

2.4.1 Fine-Grained Sentiment Classification

This technique categorizes text into multiple sentiment categories beyond simple positive, negative, or neutral labels. LSTM networks trained for fine-grained sentiment classification classify text into more nuanced sentiment classes, such as very positive, positive, neutral, negative, and very negative. Fine-grained sentiment analysis provides richer insights into sentiment expressions, enabling more nuanced understanding of text sentiment.

2.4.2 Hierarchical Sentiment Analysis

Hierarchical models, including hierarchical LSTM networks, capture sentiment at different levels of granularity within text. Hierarchical LSTM models first analyze document-level sentiment and then further analyze sentence-level sentiment within documents. This hierarchical approach facilitates a comprehensive understanding of sentiment patterns across different levels of text granularity.

3.2 Requirement Analysis

The various hardware and software requirements, datasets used, and evaluation metrics are mentioned in detail in this section.

A. **Technical Implementation Requirements**

The experiment setup is carried out on a computer system which has the different hardware and software specifications as given in Table 3.2 and Table 3.3 respectively.

Table 3.1 Hardware details

Processor	Intel(R)Core (TM) i5-9300H CPU @ 2.40GHz
HDD	180 GB
RAM	2 GB

Table 3.2 Software details

Operating System	Windows 11
Programming Language	Python, Javascript
Database	Sqlite3

B. **Dataset**

The "suicide_detection.csv" dataset consists of a collection of textual data, with each text sample labeled as either "suicide" or "non-suicide". With the textual content acting as the input features and the binary classification labels assisting in the development of predictive models that can automatically identify instances of suicidal content within the text, this dataset is intended for use in training and assessing machine learning models for suicide detection. The dataset is useful for mental health and suicide prevention research and applications because it enables the creation of sentiment analysis and text-based detection algorithms that aid in early intervention and support initiatives.

Dataset used	**No. of posts**	**No. of categories**
Suicide and Depression Detection	116037 suicide-related posts and 116037 non-suicide-related posts.	2

C. Evaluation Metrics

C.1 Standard Datasets Used

The "suicide_detection.csv" dataset consists of a collection of textual data, with each text sample labeled as either "suicide" or "non-suicide". With the textual content acting as the input features and the binary classification labels assisting in the development of predictive models that can automatically identify instances of suicidal content within the text, this dataset is intended for use in training and assessing machine learning models for suicide detection. The dataset is useful for mental health and suicide prevention research and applications because it enables the creation of sentiment analysis and text-based detection algorithms that aid in early intervention and support initiatives.

C.2 Evaluation Metrics

Accuracy: 92.3% accuracy was attained by the model. This metric shows what percentage of the dataset's total number of instances were correctly classified. With an accuracy of 92.3%, the model performs reasonably well overall.

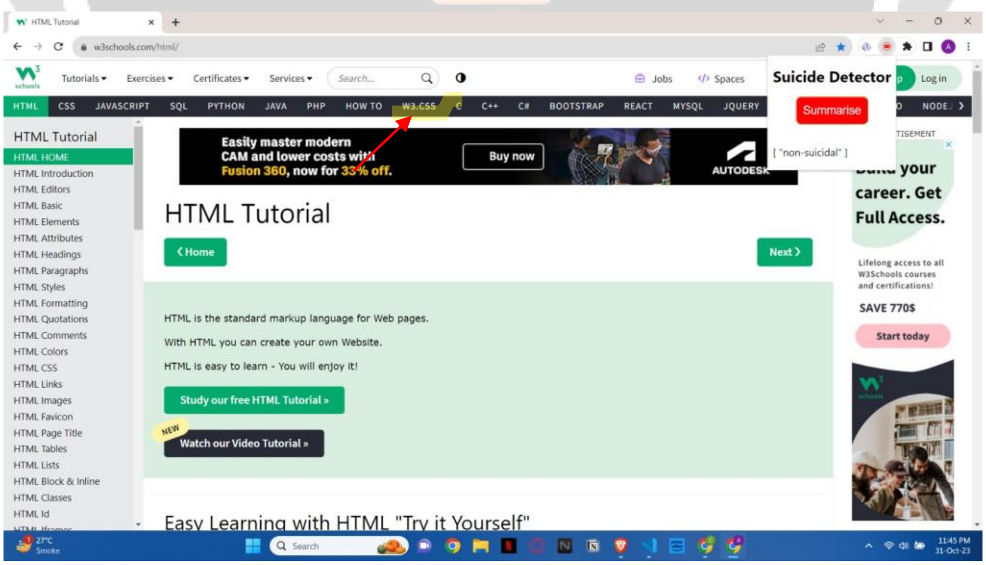
Precision: The model's precision stands at 91.56%. Out of all the positive predictions the model makes, precision measures the percentage of true positive predictions (suicides that are correctly identified). With a precision of 91.56%, the model appears to have very accurate positive predictions.

Recall: The recall is 93.21%. Recall measures the percentage of accurate positive predictions among all real positive occurrences in the dataset. The model is successful in identifying a sizable percentage of real suicide cases, as evidenced by its 93.21% recall rate.

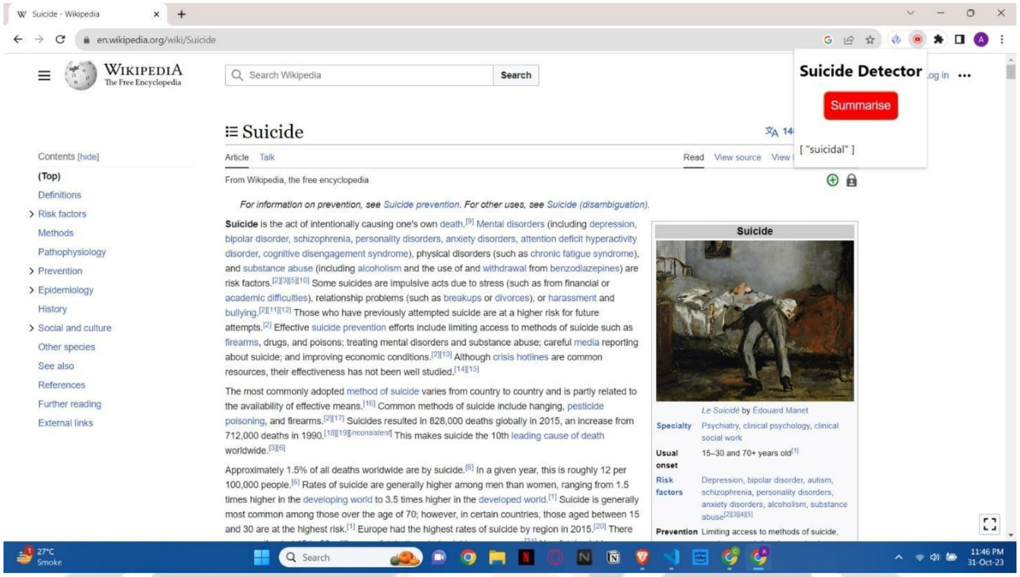
4. Result and Analysis

The process begins with a browser extension installed on the user's web browser. This extension extracts information from the user's browsing history, including visited websites and page titles. The data extracted is then passed on to a Flask backend. The Flask backend plays a crucial role in orchestrating the process. It triggers a web scraper, which is responsible for accessing the content of the web pages visited by the user. The scraper collects text and other relevant data from these web pages. The scraped data is then transmitted to a classifier, a key component in this project. The classifier is designed to analyze the collected data and apply machine learning algorithms to classify it that may indicate signs of suicidal behavior or distress. This classification could include factors such as the frequency of visits to mental health websites, the use of specific keywords, or patterns of behavior that deviate from the norm

Non-Suicide detection:



Suicide detection:



5. Conclusion

In this project, we have designed a comprehensive system for suicide detection using a person's web browsing history. The methodological approach involves a series of interconnected components to identify potential indicators of suicidal behavior. The process involves a browser extension extracting user browsing history data, which is then sent to a Flask backend for analysis. The backend triggers a web scraper, which collects relevant data from visited websites. The data is then sent to a classifier, which uses machine learning algorithms to classify it indicating suicidal behavior or distress. In conclusion, this project combines web technology, data analysis, and machine learning to address a critical issue of mental health. It has the potential to assist in suicide prevention by alerting individuals, mental health professionals, or support networks to signs of distress in an individual's online behavior. However, it is essential to consider ethical and privacy concerns while implementing such a system and to collaborate with mental health experts to ensure that appropriate interventions are in place to support those at risk.

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7. References

[1] Matthew Mulholland, Joanne Quinn (2012) Suicidal Tendencies: The Automatic Classification of Suicidal and Non-Suicidal Lyricists Using NLP

[2] John Young, Steven Bishop a, Carolyn Humphrey a, Jeffrey M. Pavlacic b. (2023) A Review of natural language processing in the Identification of suicidal behavior.

[3] Farsheed Haque, Ragib Un Nur, Shaeekh Al Jahan, Zarar Mahmud, and Faisal Muhammad Shah (2020) A Transformer-Based Approach to Detect Suicidal Ideation Using Pre-Trained Language Models.

[4] Arunima Roy, Katerina Nikolitch, Rachel McGinn, Safiya Jinnah, William Klement, and Zachary A.

Kaminsky (2020) A machine learning approach predicts future risk of suicidal ideation from social media data.

[5] *Wesllei Felipe Heckler, Juliano Varella de Carvalho, Jorge Luis Victória Barbosa (2022) Machine Learning for suicidal ideation identification: A systematic literature review.*

[6] *Michael Mesfin Tadesse, Hongfei Lin, Bo Xu, and Liang Yang (2019) Detection of Suicide Ideation in Social Media Forums Using Deep Learning.*

[7] *Abayomi Arowosegbe, Tope Oyelade, and Paul B. Tchounwou (2023) Application of Natural Language Processing (NLP) in Detecting and Preventing Suicide Ideation.*

[8] *Rezaul Haque, Naimul Islam, Maidul Islam, and Md Manjurul Ahsan (2022) A Comparative Analysis of Suicidal Ideation Detection Using NLP, Machine, and Deep Learning*

[9] *Liuling Mo,He Li, and Tingshao Zhu (2022) Exploring the Suicide Mechanism Path of High- Suicide-Risk Adolescents—Based on Weibo Text Analysis.*