Detecting Suicide Risk and Exploring Contributing Factors: Classification and Topic Modeling of Social Media Data

Evan Dan, Jianfeng Zhu, Ruoming Jin
Department of Computer Science,
Kent State University
Kent, USA
e-mail: edan1@kent.edu, jzhu10@kent.edu, rjin1@kent.edu

***Abstract*—Suicide remains a critical global health issue, with over 700,000 lives lost annually. Existing research has explored factors influencing suicidal thoughts, but traditional studies often rely on small-scale data sources that may overlook contextual influences. This study aims to address that gap by analyzing a large dataset of posts from Reddit communities r/SuicideWatch and r/Teenagers to detect suicidal ideation and identify associated themes. Using Natural Language Processing and statistical methodologies, including Llama 3-8b and Mistral-7b, we fine-tuned models with manually labeled data to improve classification accuracy of posts for suicidal ideation. Using data re-labeled by the large language models, BERTopic identified key themes linked to suicidal ideation: relationship struggles, academic stress, and family trauma. While non-suicidal posts also included social and academic concerns, the topics were centered around more immediate stressors rather than the long-term emotional distress issues seen in the suicidal group. These findings highlight the potential of NLP methodologies in analyzing large-scale social media data, offering valuable insights for informing new prevention strategies. Additionally, social media, in combination with NLP, serves as a valuable outlet for capturing genuine emotional struggles, enabling more timely and personalized mental health support compared to traditional approaches like counseling.**

Keywords-Suicide; The Llama 3-8b; Mistral-7b; GPT-4o; Reddit; BERTopic Modeling; contributing factors.

I. INTRODUCTION

Each year, 726,000 people around the world lose their lives to suicide, with many more attempting it daily [1]. Youth are particularly vulnerable, with suicide being the second leading cause of death for those in aged 10–14 and 25–34 years and the third leading cause for individuals aged 15–24 years in the U.S. in 2022 [2][3]. However, beyond impacting the conflicted individuals, suicide also leaves lasting effects on these individuals' families and communities. A survey conducted by Cerel et al on 1,736 adults in Kentucky found that suicide-exposed individuals, those personally affected by suicide, were twice as likely as unexposed individuals to meet screening criteria, which assess mental health symptoms, for depression and nearly twice as likely for anxiety [4]. Additionally, suicide is driven by various social, cultural, biological, psychological, and environmental factors that span a lifetime. By examining child suicide cases from the National Violent Death Reporting System, Ruch et al identified four key themes: mental health and suicide concerns (31.4%), traumatic experiences (27.1%), family challenges (39.8%), and school or peer difficulties (35.6%) [5]. Building on this, Turecki et al emphasized the interplay of genetics, personality traits, psychiatric illnesses, and environmental influences in suicide risk [6].

Although these studies offer important insights, conventional tools such as questionnaires and surveys present challenges in thoroughly uncover and examine the complexities of suicidal factors. Due to limitations like structured response formats, inherent biases, and the absence of dynamic, real-time data, these methods frequently fall short in capturing the nuanced feelings and experiences of individuals with suicidal ideation [7]. Furthermore, research based on suicide reporting databases often focus on deaths by suicide, excluding data on non-fatal suicide attempts or suicidal ideation, which are critical for understanding the full spectrum of suicidal behavior. However, studies have demonstrated that non-fatal suicide attempts are significant predictors of future suicide risk, with research by Turecki et al indicating that past suicide attempts increase the likelihood of subsequent suicidal behavior [6]. In other words, these data sources often lack the depth and scope needed to fully understand the range of suicidal behaviors, including nuanced emotions and non-fatal attempts, which are critical for assessing future suicide risks.

On the other hand, as social media, especially Reddit, play a growing role in mental health discussions, they have emerged as promising data sources due to its role in fostering open discussions. Reddit, with over 97 million daily active users [8], features mental health subreddits like r/SuicideWatch (512K+ members), where users can share feelings and seek help [9]. Its anonymity and diverse subcommunities encourage users to discuss sensitive topics more openly, making it a unique platform for gathering authentic mental health data, as highlighted by Yeskuatov et al [10]. This was exemplified during the COVID-19 pandemic, when Reddit saw spikes in posts about health anxiety, economic stress, social isolation, and substance use [11][12][13], providing valuable insights into mental health trends. These studies underscore the platform's potential in providing crisis support and fostering connection during challenging times.

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Building on the potential of innovative data sources like Reddit, recent research has also highlighted the importance of advanced analytical approaches to better understand and predict suicidal behaviors. For instance, Franklin et al.'s meta-analysis called for the use of complex Machine Learning (ML) models to enhance predictive accuracy in identifying suicidal thoughts and behaviors [14]. Advancements in ML and Natural Language Processing (NLP) offer promising tools for analyzing mental health data and identifying patterns related to suicidal behaviors [15], facilitating deeper exploration of mental health discussions on platforms like Reddit. For instance, Bauer et al utilized large language models (LLMs) to analyze Reddit posts, revealing patterns of disconnection, hopelessness, and trauma in users experiencing suicidality [16]. Expanding on these approaches, BERTopic, developed by Grootendorst, offers several advantages over traditional clustering regression techniques [17]. BERTopic has been used to detect signs of depression on Reddit, analyze public sentiment towards artificial intelligence (AI) in mental health, and track mental health trends during the COVID-19 pandemic [18][19][20], demonstrating its potential for advancing mental health research.

Traditional research on suicide risk has largely depended on standardized survey methods or government datasets, which often fall short in representing the emotional complexity of individuals struggling with suicidal thoughts. These methods tend to focus narrowly on isolated factors, overlooking the intricate and interconnected nature of suicidal behaviors. In contrast, our study leverages a substantial dataset of Reddit posts from r/SuicideWatch and r/Teenagers, enabling access to vast, real-time, and unfiltered expressions of emotional states. By utilizing advanced LLMs, such as Llama 3-8b and Mistral-7b, coupled with sophisticated topic modeling techniques, we were able to identify nuanced factors associated with suicidal thoughts, classify posts as suicidal or non-suicidal with precision, and uncover detailed themes within these categories. This approach overcomes the limitations of traditional datasets, providing a deeper, more comprehensive understanding of suicide-related behavior. The use of large language models allows us to capture intricate patterns, emotional nuances, and contextual insights that are otherwise inaccessible through conventional methods. By expanding the scope of analysis and enhancing its depth, our findings provide actionable, evidence-based strategies to inform suicide prevention efforts and foster meaningful advancements in the field.

The main contributions of this paper can be summarized as follows:

1. Demonstrated value of using Natural Language Processing methodologies, including fine-tuning Llama 3-8b and Mistral-7b, for analyzing social media data regarding suicidal ideation, a topic full of complex nuances.
2. The Llama 3-8b model achieved a test accuracy of 0.9371 for classifying Reddit posts for suicidal ideation, demonstrating its ability to capture detailed emotional patterns.
3. Using BERTopic, we revealed key topics in the discussions within the classified suicidal and non-suicidal Reddit posts.

The rest of this paper is organized as follows. Section II provides a thorough description of the data preprocessing and analysis methods, detailing the cleaning process, classification models, evaluation metrics, and topic modeling approaches. Section III presents and discusses the main findings. Section IV finishes the paper with the conclusions.

II. METHODS

This next section will detail the specific steps taken within the study to reach the analysis results obtained.

A. Data Collection and Preprocessing

This study utilized a Kaggle dataset compiling posts from December 16, 2008, to January 2, 2021, sourced from the subreddits r/SuicideWatch and r/Teenagers. The dataset uploader, Komati, anonymized the usernames for pseudonymity [21]. The data was then preprocessed to improve analysis accuracy. We employed the Pandas library to streamline analysis by arranging the unprocessed data into structured data frames [22]. Regular Expressions (RegEx) was applied to remove repetitive filler text, unnecessary whitespace (newlines, spaces, tabs), and URLs, while also converting all text to lowercase to maintain consistency within the data [23]. Similarly, we utilized the Unidecode library to remove accented characters [24]. In addition, contractions were converted to their complete forms using the Contractions library [25] while lemmatization, the process of transforming words to their base forms, was applied using the NLTK library [26].

In the original dataset, posts were categorized as “suicide” or “non-suicide” based on the subreddit they originated from [21]. However, there were inaccuracies with this labeling, so we re-classified the posts to improve the accuracy of the labels using large LLMs. We first manually labeled approximately 900 posts as “suicidal” or “non-suicidal” according to the definition of “suicidal ideation” from the Diagnostic and Statistical Manual of Mental Disorders [27]. Afterwards, the hand-labeled data was divided into three partitions: 80% of the data for training, 10% of validation, and 10% for testing. Two LLMs, Llama 3-8b and Mistral 7-b, were trained on this data, and the more accurate model was selected to re-label the full dataset.

B. Detection and Classification Models

Llama 3-8B is an advanced LLM developed by Meta and was released in April of 2024. Consisting of 8 billion parameters, it can interpret and classify textual data effectively. It was pretrained on 15 trillion tokens of publicly available data, with the data having gone through Llama 2 models and advanced data-filtering pipelines to ensure their high quality [28]. Additionally, with methods such as supervised fine-tuning (SFT) and reinforcement learning with human feedback (RLHF), Meta was able to ensure the model provides accurate responses while prioritizing safety [29]. Because of the extensive pretraining, Llama 3-8B is well-suited for identifying complex patterns and nuanced meanings in textual data, making it an ideal tool for classifying Reddit posts.

Released in October of 2023, Mistral 7B is an advanced LLM that was developed by Mistral AI [30]. The model contains 7.3 billion parameters and is designed for both speed and precision for Natural Language Processing (NLP) tasks. The model incorporates innovative mechanisms such as Grouped-Query Attention (GQA) and Sliding Window Attention (SWA). GQA is an optimization technique that reduces computational complexity and enhances the efficiency of predictions [31]. Meanwhile, SWA enables the model to process longer text inputs at a manageable computational cost. Demonstrated in Figure 1, it achieves this by employing a sliding window that restricts the model's focus to a small segment of the input at a time. By processing many of these windows individually and sliding them across the input sequence, the model can utilize its multiple transformer blocks to identify indirect relationships between tokens across these segments. This approach ensures it can effectively comprehend the contexts of long inputs while maintaining computational efficiency [30]. With these methods, Mistral 7B is well-suited for classifying the Reddit posts as features such as the SWA make it ideal for capturing nuanced patterns often present in lengthy posts.

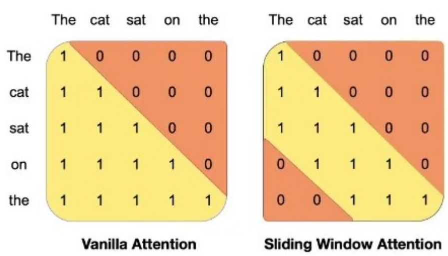

Figure 1. Sample Demonstration of SWA [30].

The Llama 3-8b and Mistral-7b models were each trained on manually labeled posts for three epochs with a learning rate of 0.0002. To assess the effectiveness of the final model, we employed standard evaluation metrics, including accuracy, precision, recall, and F-1 scores. These metrics are defined using four key terms that are defined below.

- **True Positive (TP):** Model correctly identifies a suicidal post as suicidal.
- **True Negative (TN):** Model correctly identifies a non-suicidal post as non-suicidal.
- **False Positive (FP):** Model incorrectly identifies a non-suicidal post as suicidal (Type 1 Error).
- **False Negative (FN):** Model incorrectly identifies a suicidal post as non-suicidal (Type 2 Error).

Accuracy measures the overall proportion of correct predictions with a ratio of all correctly classified posts to the total number of posts [32]:

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

Precision measures the proportion of predicted positive cases that are correct [32] with a ratio of correctly classified suicidal posts to all posts predicted as suicidal (including both correctly and incorrectly identified suicidal posts):

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

Recall assesses the portion of actual positive cases that are identified correctly [32] with a ratio of correctly classified suicidal posts to all posts from r/SuicideWatch (including both correctly identified suicidal posts and incorrectly identified non-suicidal posts):

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3)$$

In situations where there is a high cost associated with false-negative prediction; recall proves to be very useful for identifying the best model [33]. Between false positives and false negatives, it is most likely less consequential to incorrectly predict someone as suicidal than to incorrectly predict a suicidal person as non-suicidal.

F1-Score is the harmonic mean of precision and recall [32]. In other words, the F1-Score is an average of the two metrics:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

To evaluate the status of the models during the fine-tuning process, we utilized training loss and validation loss scores. After completing the fine-tuning, we selected the versions of the Llama 3-8B and Mistral 7B models with the lowest losses to test against the test dataset to ensure optimal performance. The model with the higher test accuracy was then used to classify the rest of data for suicidal ideation. Finally, the processed and re-labeled dataset was separated into two categories based on the suicide/non-suicide label. This step enables targeted analysis focused on addressing the research objectives of understanding factors associated with suicide, as this allows us to analyze and compare results between the two groups.

C. BERTopic

To analyze the re-classified data, BERTopic was employed for topic modeling to uncover key themes within the posts. The model incorporates BERT embeddings, improving its capacity to detect subtle patterns and capture nuanced sentiments within the dataset [17]. Additionally, by utilizing contextual term frequency-inverse document frequency (c-TF-IDF), BERTopic ensures precise clustering of topics with meaningful and coherent groupings. The analysis was applied to each group of classified posts, "suicidal" and "non-suicidal", facilitating a thorough comparison of their characteristics and providing deeper insights into the themes specific to each group. In addition, we included the KeyBERTInspired model [34] to filter out stopwords, improving the topics' precision of the clusters. We also incorporated OpenAI's GPT-4o [35] to generate specific and detailed topic labels, enhancing the clarity and interpretability of the identified themes. The following prompt was used to guide the labeling process:

I have a topic that contains the following documents: [DOCUMENTS]

The topic is described by the following keywords: [KEYWORDS].

On the basis of the information above, extract a short but highly descriptive topic label. Make sure it is in the following format: topic: <topic label>.

III. RESULTS

Table I showcases examples of posts before and after processing, highlighting the impact of the cleaning process. In the cleaned versions, the texts exhibit a more uniform and consistent structure while retaining the original sentiments of the posts.

TABLE I. SAMPLE OF DATA PREPROCESSING

Class	Text before and after pre-processing	
	Original Post	***Cleaned Text***
non-suicide	Finally 2020 is almost over... So I can never hear "2020 has been a bad year" ever again. I swear to fucking God it's so annoying	finally 2020 is almost over.. so i can never hear "2020 has been a bad year" ever again. i swear to fucking god it is so annoying
non-suicide	i need help just help me im crying so hard	i need help just help me i am crying so hard
suicide	It ends tonight.I can't do it anymore. \nI quit.	it end tonight.i can not do it anymore. i quit.
suicide	Been arrested - feeling suicidal Edit	been arrested - feeling suicidal edit

A. Model Performance

Model performance for Llama 3-8B and Mistral-7B model can be seen in Table II below. With slightly a slightly higher accuracy, recall, and F1 score, the Llama 3-8B model outperformed the Mistral-7B against the test dataset, so the Llama 3-8B model was selected to re-label the remaining data. Afterwards, the model re-labeled 96,086 posts as "suicidal" and 135,988 posts as "non-suicidal".

TABLE II. MODEL PERFORMANCE COMPARISON

Model	Test Performance			
	Accuracy	*Recall*	*Precision*	*F1 Score*
Llama 3-8b	0.9371	0.9371	1.000	0.9676
Mistral-7b	0.9314	0.9314	1.000	0.9645

B. Key Topics Identified by BERTopic

To address the goal of uncovering themes linked to suicidal thoughts, this study employed BERTopic to analyze both suicidal and non-suicidal posts. For analysis, we concentrated on specific topics of concerns to align with the study's aim of investigating the underlying factors associated with suicidal thoughts.

By focusing on these themes, the analysis maintains a strong commitment to the research objectives. Table III highlights the top 10 topics of concern identified for the suicidal group while Table IV displays the top 10 topics of concern for the non-suicidal group.

Expanding on the top 10 topics identified by BERTopic in Table III, three critical themes emerged related to sources of mental instability across various life stages: relationship struggles affecting adults' emotional health, academic stress impacting students' self-esteem, and family trauma influencing childhood development. The most common theme in the suicidal group was centered around struggles and emotional turmoil from relationships (3,285 posts), suggesting that difficulties in maintaining or coping with personal relationships may contribute to feelings of hopelessness often associated with suicidal ideation. The emotional attachment and dependence involved in romantic relationships can lead to profound loneliness or a loss of self-identity when disrupted, prompting some to contemplate suicide. Afterwards, academic pressures emerged as the second most common topic (1,791 posts), illustrating how the fear of failure can contribute to feelings of anxiety and hopelessness, especially among students. This finding may reflect the increased academic demands and societal expectations placed on students, which can result in feelings of inadequacy. Another prominent theme, the childhood and family trauma topic (1,421 posts) underlines the lasting impacts of early life experiences on mental health. Such traumas can contribute to complex emotional issues and unresolved feelings that may intensify over time, particularly as individuals face adulthood. When compounded by present-day struggles, these lingering effects can potentially trigger suicidal thoughts.

TABLE III. TOP 10 TOPICS IN SUICIDAL POSTS

Rank	Topics	
	Suicide Topic (n=39742)	***Count***
1	Experiencing emotional struggles and breakups in relationships	3285
2	Struggles with academic failure and mental health	1791
3	Childhood and family trauma	1421
4	Emotional dilemmas with suicide	1273
5	Suicidal intent with overdosing on pills	878
6	Struggles with loneliness and low self-esteem	856
7	Suicidal farewell messages	787
8	Self-harm and suicidal ideation	538
9	Depressed birthdays and suicidal thoughts	392
10	Suicidal intents with firearms	347

Moreover, themes such as "Emotional Dilemmas with Suicide" (1,273 posts) and "Suicidal Intent with Overdosing on Pills" (878 posts) reveal that some users are not only coping with underlying struggles but are also directly confronting the act of suicide itself. These users express deep internal conflicts about their thoughts or contemplate specific methods, reflecting the internal turmoil between the desire to escape emotional pain and the emotional, moral, or religious beliefs that deter them from acting on suicidal impulses.

Additionally, the topics of loneliness and low self-esteem (856 posts) and self-harm (538 posts) suggest that personal insecurities, such as feelings of isolation and worthlessness, may exacerbate mental health struggles and contribute to suicidal ideation. These themes may point to specific psychological patterns that may serve as focal points for early intervention and tailored support strategies, as feelings of worthlessness can contribute to fragile mental states, while self-harm behaviors can escalate into the risk of suicidal thoughts. Moreover, the "Suicidal Farewell Messages" topic (787 posts) and the "Suicidal Intents with

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Firearms" topic (347 posts) highlight further expressions of extreme distress experienced by some individuals. Given the lethality of firearms and the commitment reflected in discussions of suicide notes, these topics may suggest progression from ideation to preparation, revealing the importance of identifying these specific signals to prevent further progression through timely intervention.

TABLE IV. TOP 10 TOPICS IN NON-SUICIDAL POSTS

Rank	Topics	
	Non-suicide Topic (n=63885)	*Count*
1	Exploring and managing dynamics in romantic relationships	6711
2	Concerns with boredom and loneliness	3286
3	Academic struggles for college students	1813
4	Struggles with parents and family dynamics	1121
5	Sexual frustrations	611
6	Challenges in socializing for introverts	536
7	Challenges with sleeping and persistent insomnia	440
8	Issues related to racism and discriminatory language	431
9	Concerns with alcohol consumption	407
10	Struggles of transgender identity	393

By comparison, while non-suicidal posts in Table IV reflect significant challenges, they do not indicate immediate crises but reflect more general concerns of teenagers and young adults. Comparing these two sets of topics reveals some thematic overlaps, including topics regarding romantic relationship struggles, academic pressures, and family dynamics, which are experienced and expressed in distinct ways by each group. In the suicidal posts, these themes are often associated with feelings of hopelessness, personal failure, or a desire to escape, whereas, in non-suicidal posts, the same issues appear to provoke irritation, uncertainty, or a desire for improvement. For instance, the topic regarding relationship struggles for suicidal posts is more centered toward long-term emotional distress, whereas the corresponding topic for non-suicidal posts reflects a focus on exploring emotional dynamics and personal growth within relationships. Similarly, the academic topic in the non-suicidal group is geared more towards daily struggles, whereas the topic for the suicidal group reveals deeper feelings of perceived failure accompanied by intense self-criticism.

Broader social and personal concerns such as discussions about racism and transgender identities highlight personal challenges in managing mental and emotional well-being, while topics such as boredom and loneliness demonstrate feelings of disconnection and a lack of purpose. While these topics do not explicitly indicate suicidal ideation, they may represent underlying problems that could escalate into more severe issues more, such as low self-esteem, which are more commonly observed in suicidal posts. In contrast, themes regarding farewell messages and detailed suicide planning point to a deeper level of emotional distress, reflecting a serious stage of suicidal intent.

This comparison indicates the importance of understanding context and intensity within mental health discussions. Interventions for suicidal individuals should prioritize crisis management and emotional support tailored to severe psychological distress. For non-suicidal individuals, interventions might instead focus on counseling, life skills training, and support networks that help them manage common stressors before they become more severe.

IV. CONCLUSIONS

This study demonstrates the effectiveness of advanced NLP and statistical techniques in identifying and analyzing suicidal ideation based on large-scale social media data from Reddit. By fine-tuning Llama 3-8B, Mistral 7B, and BERTopic, we revealed key sources of mental instability associated with suicidal thoughts, including relationship struggles, academic stress, and family trauma. The findings also highlighted distinct thematic differences between posts indicating suicidal ideation and general adolescent concerns, revealing deeper insights into specific triggers and expressions of suicidal thoughts among young individuals. Our results underscore the potential of NLP in real-time mental health monitoring and intervention on social media. Fine-tuned models, such as Llama 3-8B, which achieved a test accuracy of 0.9371, demonstrate strong predictive performance, offering scalable tools for distress detection. By addressing warning signs before they escalate into crises, these systems can provide early interventions in teenage communities, leveraging the thematic overlaps between suicidal and non-suicidal groups to design broader mental health support initiatives. To enhance model accuracy, future research could incorporate data from a wider range of social media platforms to improve generalizability while also exploring the influence of digital interactions on users' mental health. Expanding this work will offer deeper insights into the evolving role of social media in mental health and help develop targeted intervention strategies tailored to specific online behaviors and mental health challenges.

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