CAPSTONE PROJECT 1
Planning Document

Sentiment Sense: Enhancing Mental Health Support with Sentiment Analysis Methods

by

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1.0 Introduction

1.1 Background of the Study

The global prevalence of mental health issues has significantly risen, leading more individuals to seek help online rather than through conventional channels. The internet's anonymity and accessibility offer a haven for those hesitant to pursue face-to-face therapy or counseling. Social media platforms, forums, and online communities have become spaces where people openly express their emotions and struggles. Sentiment analysis, a technique that involves evaluating opinions and emotions expressed in text data, has shown promise in aiding mental health issues. By analyzing sentiments and emotions from various sources such as social media, researchers have been able to develop models for diagnosing common mental disorders (Zhou et al., 2019). This approach can provide valuable support for the prevention and early diagnosis of mental health conditions. Furthermore, sentiment analysis has been utilized to assess mental health status through written language and to identify communities in need of mental health services post natural disasters (Aguilar & Baek, 2020). In the context of mental health evaluation, sentiment analysis can be particularly beneficial for specific groups such as healthcare workers who may face increased risks and stressors (Samuel et al., 2020).

By analyzing sentiments expressed in social media data, sentiment analysis can offer insights into emotional well-being and provide a non-intrusive method for measuring academics' well-being (Müller, 2024). Additionally, sentiment analysis can help in understanding public perceptions and responses to mental health concerns, aiding policymakers in developing effective strategies (Chen & Kwak, 2022). Moreover, sentiment analysis has been applied to assess societal emotional resilience to natural disasters and to understand human emotions and behaviors during pandemics (Bathina et al., 2022; Saraff et al., 2018). By leveraging sentiment analysis on social media content, researchers have been able to gauge emotional responses to crises and disasters, providing valuable insights into the mental well-being of individuals affected by such events (Lim et al., 2018).

In conclusion, sentiment analysis offers a valuable tool for understanding and addressing mental health issues by analyzing sentiments and emotions expressed in text data. By leveraging sentiment analysis techniques, researchers and practitioners can gain insights into emotional well-being, diagnose mental disorders, identify at-risk communities, and develop strategies to support mental health effectively.

1.2 Problem Statement

The application of sentiment analysis in the context of mental health presents several challenges that need to be addressed. One of the primary issues in sentiment analysis for mental health is the need for more nuanced analysis to capture the complexity of human emotions accurately (Valdez et al., 2020). While sentiment analysis can provide insights into mood and sentiment, it may not always fully capture the intricacies of mental health conditions (Xavier & Lambert, 2022). Emotions and sentiments expressed in text data are essential indicators of mental states, but they may not always be definitive markers of mental health progression (Xavier & Lambert, 2022). Another significant problem statement in sentiment analysis for mental health is the requirement for more sophisticated models that can differentiate between various emotional states and their implications for mental well-being (Datta et al., 2019). Current sentiment analysis models may struggle to predict emotional states and vulnerability accurately, limiting their effectiveness in mental health applications (Datta et al., 2019). Additionally, the use of sentiment analysis in mental health requires careful consideration of the type of analysis performed to ensure nuanced aspects of sentiment are captured (Valdez et al., 2020). Furthermore, there is a need for sentiment analysis models to account for cultural and contextual differences in expressing emotions related to mental health (Yin et al., 2022). Different cultures may have unique ways of describing and perceiving mental health issues, which can pose challenges for sentiment analysis models developed based on a specific cultural context (Yin et al., 2022). To enhance the effectiveness of sentiment analysis in mental health, it is crucial to consider cultural nuances and adapt models accordingly. In conclusion, the challenges in sentiment analysis for mental health include the need for more nuanced analysis to capture the complexity of human emotions accurately, the requirement for sophisticated models to differentiate between emotional states, the consideration of cultural and contextual differences in expressing emotions related to mental health, and the importance of understanding the limitations of sentiment analysis in fully assessing mental health conditions.

1.3 Project Objectives

1. Analyse the sentiment patterns in the social media platform data to identify emotional experiences related to mental health challenges

2. Develop a sentiment analysis for mental health distress detection and integrate the model to the web-based platform

3. Evaluate the performance and reliability of the sentiment analysis in the context of mental health-related data

1.4 Project Scope

This project will focus on developing a sentiment analysis model for detecting indicators of mental distress in English-language online communications from social media platforms, including Twitter and Reddit, as well as dedicated mental health forums. -Additionally, the project will address ethical considerations to ensure compliance with data protection regulations. The final outcome will consist of a functional prototype of the sentiment analysis system and a comprehensive report on its performance and potential applications in mental health support.

2.0 Literature Review

Sentiment analysis, also known as opinion mining, has emerged as a powerful tool in various domains, including business, politics, and health care. This review focuses on the application of sentiment analysis in addressing mental health issues, a burgeoning area of interest as more individuals turn to online platforms to express their emotions and seek support. This literature review aims to provide a comprehensive overview of existing research on sentiment analysis for mental health, highlighting key methods, theories, and debates, and identifying gaps in the current knowledge. By synthesizing the findings from various scholarly sources, this review seeks to establish a foundation for future research and development in this critical area.

2.1 Mental Health Issues and Sentiment Analysis

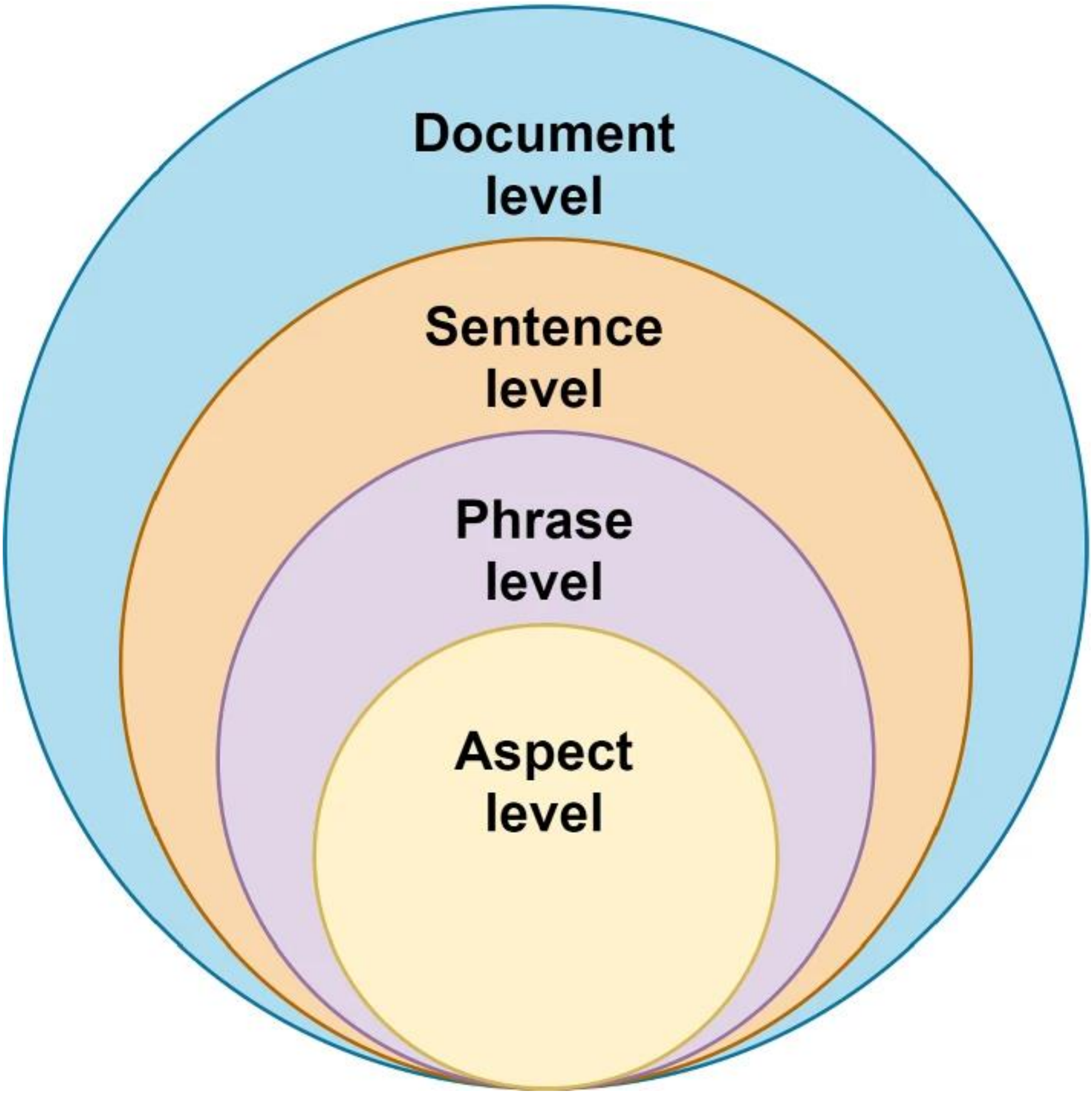
Mental health is a global concern, with millions of individuals affected by various conditions such as depression, anxiety, and bipolar disorder. Despite the increasing awareness and resources available, many people are still reluctant to seek professional help due to stigma, lack of access, and other barriers (Corrigan, 2004). Consequently, the internet has become a refuge where individuals can express their emotions and seek anonymous support. Online platforms such as social media, forums, and blogs have become rich data sources for analyzing mental health trends and providing timely interventions.

Sentiment analysis can play a crucial role in this context by automatically identifying and interpreting emotions expressed in text (Pang & Lee, 2008). This technology can help detect early signs of mental health issues, track the progression of conditions, and provide insights for mental health professionals and researchers.

2.1.1 Sentiment Analysis: Explanation

Sentiment analysis involves the use of natural language processing (NLP), text analysis, and computational linguistics to identify and extract subjective information from text sources. The primary goal is to determine the sentiment expressed in a given piece of text, which can range from positive to negative or neutral.

2.1.2 Levels of Sentiment Analysis



Img1 from (Wankhade et al., 2022).

Sentiment analysis include several levels which are sentence levels, document level, and aspect level.

Positive, negative, or neutral polarity (sentiment) is assigned at the document level, where the document is viewed as a single entity. This type of sentiment analysis is not used a lot. At this level, both supervised and unsupervised learning methods can be employed to classify the document. However, two of the most significant challenges in document-level sentiment analysis are dealing with cross-domain and cross-language scenarios (Wankhade et al., 2022). This level is useful for analysing news articles, and blog posts where the overall sentiment of the whole document is of interest. However, it may miss out on nuances where different sections of the document express different sentiments (Pang & Lee, 2008).

Sentence level is particularly beneficial when a document contains a variety of sentiments, each with different nuances (Yang and Cardie, 2014). This level of classification is linked to identifying subjective content (Rao et al., 2018). This level involves evaluating the sentiment of individual sentences within a document. Each sentence's polarity is determined separately using the same methodologies as those used at the document level, but it requires more training data and processing resources. The polarity of each sentence can then be combined to determine the overall sentiment of the document or analyzed individually (Wankhade et al., 2022). Sometimes, document-level sentiment analysis does not provide enough detail for certain applications (Behdenna et al., 2018). This approach is particularly useful for analyzing social media posts, feedback comments, and customer reviews where each sentence might express a distinct sentiment. However, it presents challenges when dealing with compound sentences or sentences that convey mixed sentiments (Liu, 2012).

At the phrase level, sentiment analysis goes further by examining specific phrases or sub-sentences to capture the sentiment of particular expressions. This method is effective for extracting finer details in opinions, such as sentiments about specific product features mentioned within a review. It demands more advanced parsing and contextual understanding to accurately identify and interpret these phrases (Wilson, Wiebe, & Hoffmann, 2005). While document-level analysis concentrated on categorizing the entire document as subjective, either positively or negatively, sentence-level analysis is more beneficial, as a document contains both positive and negative statements. Word is the most basic unit of language; its polarity is intimately related to the subjectivity of the sentence or document in which it appears (Wankhade et al., 2022).

Finally, the aspect level, also referred to as feature-based sentiment analysis, focuses on identifying sentiments related to specific aspects or attributes within a document. This approach is essential for detailed opinion mining in reviews where customers may express varying sentiments about different features of a product or service, such as battery life, screen quality, or customer service. It requires the precise identification of aspects and the accurate association of sentiments to these aspects (Liu, 2012). Each of these levels offers unique insights: the document level provides a broad overview, the sentence and phrase levels offer more granular insights, and the aspect level delivers detailed sentiment analysis related to specific features or topics within the text.

2.2 General Approaches for sentiment classification

Lexicon-Based Approaches Lexicon-based approaches rely on a predefined list of words associated with specific sentiments. These methods are relatively straightforward and interpretable but may struggle with the nuances of human language, such as sarcasm and context (Taboada et al., 2011). One notable example is the use of the Affective Norms for English Words (ANEW) lexicon, which provides emotional ratings for a large set of words (Bradley & Lang, 1999).

Machine Learning Models Machine learning models, particularly those based on supervised learning, have shown significant promise in sentiment analysis. These models are trained on labeled datasets to learn patterns associated with different sentiments. Commonly used algorithms include Support Vector Machines (SVM), Naive Bayes, and logistic regression (Manning, Raghavan, & Schütze, 2008). More recent advances in deep learning, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have further improved the accuracy of sentiment analysis (Kim, 2014; Lai et al., 2015).

Hybrid Methods Hybrid methods combine lexicon-based approaches with machine learning models to leverage the strengths of both techniques. These methods often involve using lexicons to generate features for machine learning models or integrating rule-based systems with statistical models (Medhat, Hassan, & Korashy, 2014).

2.3 Sentiment Analysis in the Mental Health Domain (Application)

In the mental health domain, sentiment analysis has been applied to monitor and analyze the emotional states of individuals through their social media posts, clinical notes, and other text data sources. This application leverages the ability of sentiment analysis to process vast amounts of textual data quickly, providing insights that can inform mental health care strategies. For example, Gkotsis et al. (2016) analyze the language used in Reddit posts related to mental health to identify linguistic characteristics that could be useful for future applications. Social media platforms like Twitter, Facebook, and Reddit are increasingly used to communicate life experiences, providing a rich resource for understanding diseases from a patient perspective (Wicks et al., 2010; Barak et al., 2008). Studies have shown that social media data can be valuable for monitoring mental health, detecting depression, and identifying suicidal tendencies (Coppersmith et al., 2015a; De Choudhury et al., 2013; Kumar et al., 2015). For instance, Twitter data has been used to develop classifiers for recognizing depression and distinguishing between users with different mental health issues (Coppersmith et al., 2015b; Mitchell et al., 2015). Similarly, Reddit data has been used to study suicidal ideation and the Werther effect (Kumar et al., 2015).

Reddit, a widely-used social media platform, allows registered users to post queries and share information within various topic-specific forums known as subreddits. These subreddits, created and joined by users based on their interests, facilitate focused discussions on specific topics, including mental health issues (Gkotsis et al., 2016). For the analysis, the entire dataset from Reddit was filtered to identify subreddits dedicated to ten specific mental health conditions. The dataset was then divided into two categories: posts and comments. This distinction was preserved to enable targeted analysis. Posts represent the initial statements made by users to start discussions, while comments are responses to these posts, structured in a hierarchical manner. Both posts and comments can be contributed by any user, including the one who initiated the post (Gkotsis et al., 2016).

Table1 From (Gkotsis et al., 2016)

subreddit	#posts	#comments	#comments/#posts	#total
Anxiety	57,523	289,441	5.03	346,964
BPD	11,880	77,091	6.49	88,971
BipolarReddit	14,954	151,588	10.14	166,542
BipolarSOs	814	4,623	5.68	5,437
OpiatesRecovery	8,651	87,038	10.06	95,689
StopSelfHarm	4,626	24,224	5.24	28,850
addiction	4,360	6,319	1.45	10,679
aspergers	15,053	202,998	13.49	218,051
autism	9,470	52,090	5.50	61,560
bipolar	25,868	198,408	7.67	224,276
cripplingalcoholism	38,241	503,552	13.17	541,793
depression	197,436	902,039	4.57	1,099,475
opiates	56,492	906,780	16.05	963,272
schizophrenia	4,963	31,864	6.42	36,827
selfharm	12,476	68,520	5.49	80,996
SuicideWatch	90,518	619,813	6.85	710,331
Total	462,807	3,506,575	7.58	3,969,382

The volume of users, posts, and comments varied widely across the subreddits. As refer to table1. The depression subreddit had the largest number of communications, with approximately 1.1 million entries, whereas the BipolarSOs subreddit had the fewest, with around 5,000 entries. Generally, comments outnumbered posts, with the highest average number of comments per post observed in the opiates subreddit and the lowest in the addiction subreddit (Gkotsis et al., 2016). This methodology enabled a concentrated analysis of posts and comments within subreddits that specifically target mental health issues, providing valuable insights into the discussions and concerns of users dealing with these conditions (Gkotsis et al., 2016).

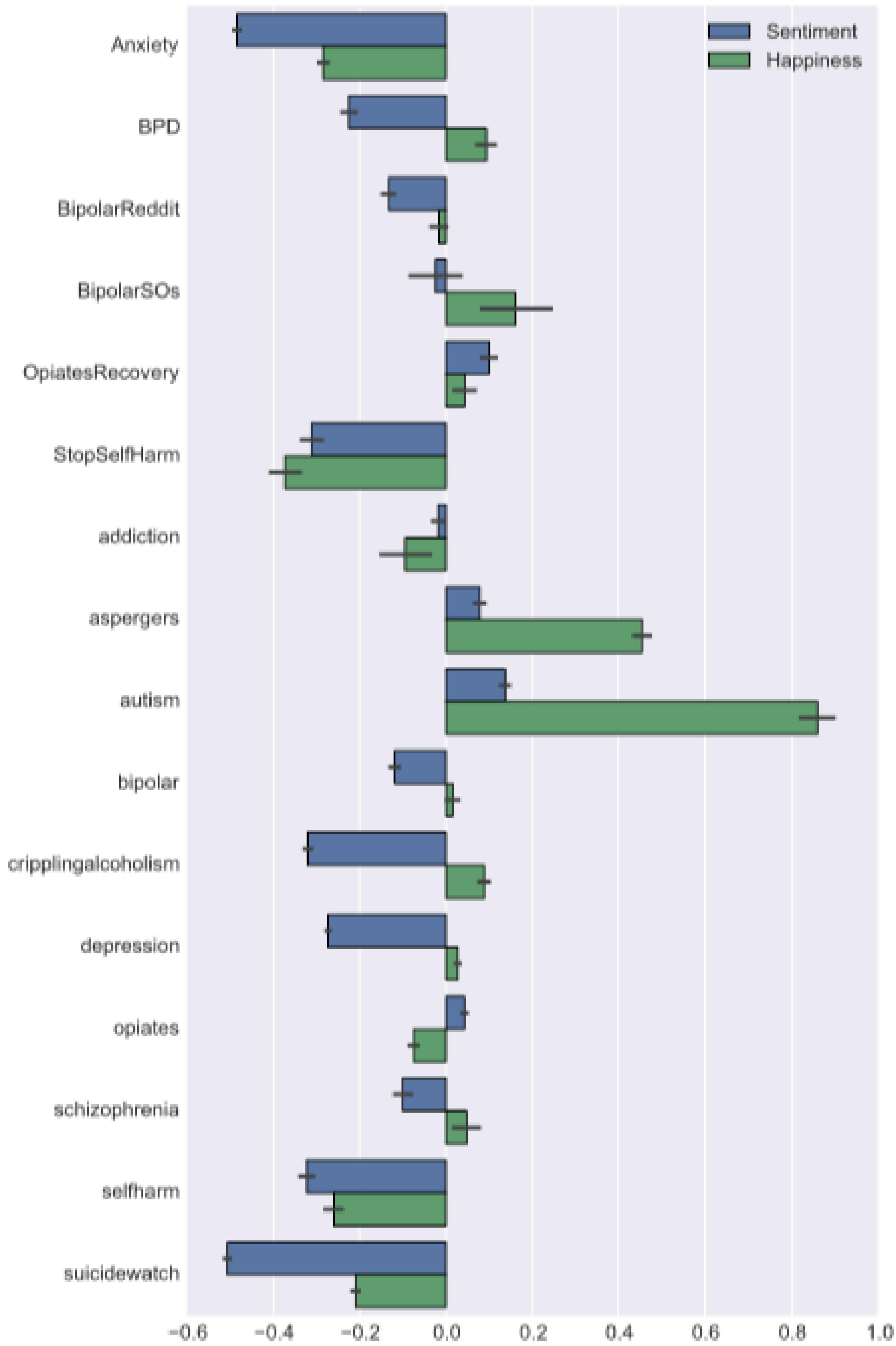
An important facet of linguistic analysis in social media communications is the assessment of sentiment. Sentiment analysis serves as a key indicator of an individual's engagement in specific events and can significantly contribute to understanding expressions of mental illness (Tausczik & Pennebaker, 2010; Murphy et al., 2015). For instance, individuals with depression often exhibit negative sentiment and express unhappiness, whereas those with Bipolar Disorder may oscillate between positive and negative sentiments. By examining sentiment and happiness across a large sample of individuals, new patterns related to mental health issues may emerge.

The study in this paper employed two distinct methods to detect sentiment (Nielsen, 2011) and happiness (Dodds et al., 2011). These methods, tailored for social media research, utilize topic-specific dictionaries. Each post in the identified subreddits was analyzed for sentiment and happiness by matching words to the dictionaries. The resulting scores were normalized based on the square root of the number of words identified in the dictionaries per post. Happiness scores were further normalized to align with sentiment values: negative values denote negative sentiment or unhappiness, positive values denote positive sentiment and happiness, and a value of zero is considered neutral (Gkotsis et al., 2016).

Our primary focus was on classifying posts rather than comments, as the latter could introduce noise that might obscure sentiment and happiness detected in posts. Given the higher volume of comments compared to posts, this decision aimed to enhance the clarity of our findings. Future research may involve more advanced linguistic techniques to refine sentiment and emotion identification (Gkotsis et al., 2016).

In essence, sentiment and happiness analysis of social media posts provides valuable insights into the mood patterns associated with various mental health conditions, highlighting the potential for developing novel understanding through linguistic assessment.
Besides, to evaluate the emotions expressed by Reddit users in subreddits related to mentalhealth issues, Gkotsis et al. (2016) employed two different methods: one for assessing general sentiment and another specifically for evaluating happiness. The results, depicted in Figure 2 of their study, reveal that, on average, a significant amount of negative sentiment is expressed across various mental health-related subreddits. Notably, posts from the "SuicideWatch" subreddit exhibit the highest levels of negative sentiment, followed by those from subreddits focused on anxiety and self-harm (Gkotsis et al., 2016).

Figure 1: A small number of subreddits show a majority of positive sentiments whereas the majority of subreddits primarily exhibit negative sentiments. In this bar plot, positive values represent positive sentiments and happiness, while negative values indicate negative sentiments or expressions of unhappiness.



Sentiment
Happiness
Anxiety
BPD
BipolarReddit
BipolarSOs
OpiatesRecovery
StopSelfHarm
addiction
aspergers
autism
bipolar
cripplingalcoholism
depression
opiates
schizophrenia
selfharm
suicidewatch
−0.6
−0.4
−0.2
0.0
0.2
0.4
0.6
0.8
1.0

Generally, sentiment and happiness expressions tend to align in direction, either positive or negative. However, there are exceptions. For instance, the "cripplingalcoholism" subreddit displays both happiness and negative sentiment. This subreddit includes posts from individuals who view alcoholism as a lifestyle choice, showcasing both the joy of overcoming addiction and the glorification of alcoholism. An example post reads: "[...] At the bottom of this pile of clothes is a full pint! How it came to rest there I don't know, but thank you Taaka gods for your gift on this day. [...]" (Gkotsis et al., 2016).

Furthermore, Figure 2 highlights a few subreddits where posts predominantly express positive sentiment. The "OpiatesRecovery" subreddit, for example, exhibits both positive sentiment and happiness. This community focuses on supporting individuals through opiate withdrawal, with users sharing their progress. Posts in this subreddit, such as "[...] I'm happy to say the shivers/flashes/heebeegeebees are a lot, lot better. Not 100% gone, but gone enough. I can deal with flashes every 4-6 hours, can't deal with them every 15 minutes. [...]" celebrate successes during withdrawal. However, even subreddits that generally lean towards happiness and positive sentiment can contain posts with negative sentiment and unhappiness.

An example from "OpiateRecovery" reads: "[...] Buying garbage from some ignorant thug to put into my fucking blood knowing how lethal it can be, but oh it couldn't happen to me. It's bizarre that after all this time of staying away I still can't fully grasp how fucking close to death I was every day. [...]" (Gkotsis et al., 2016).

In conclusion, the study by Gkotsis et al. (2016) highlights the complexity and potential of using linguistic analysis to understand mental health issues as expressed on social media platforms. The identification of discriminatory linguistic features and sentiment patterns in subreddit posts is a significant step towards more nuanced and effective mental health monitoring tools. This approach not only helps in understanding the general sentiment within different mental health communities but also offers insights into the specific needs and experiences of individuals within these groups. Future research should continue to refine these linguistic models to improve their accuracy and applicability. Incorporating more sophisticated natural language processing techniques and larger datasets could enhance the detection of subtle differences in language use among various mental health conditions. Additionally, collaboration with mental health professionals is crucial to ensure that these tools are used ethically and effectively, ultimately contributing to better mental health support and intervention strategies on social media platforms.

2.4 Comparison between Sentiment Analysis Approaches for Mental Health Applications

In the rapidly evolving field of sentiment analysis, choosing the most suitable approach is crucial, particularly for applications in mental health. Sentiment analysis techniques can be broadly categorized into lexicon-based, machine learning-based, and hybrid approaches. Each of these methods offers unique advantages and faces specific challenges, making them more or less suitable depending on the application context. This comparison aims to explore the strengths and limitations of these approaches, focusing on their effectiveness in analyzing sentiment within the mental health domain. By examining how these methodologies operate and perform, we can better understand which approach offers the most promise for enhancing sentiment analysis in mental health applications.

2.4.1 Lexicon Based Approach

Lexicon-based approaches for sentiment analysis involve using a predefined collection of tokens, each assigned a score indicating its sentiment polarity—positive, neutral, or negative (Kiritchenko et al., 2014). These scores are typically numeric, where positive tokens might be assigned +1, neutral tokens 0, and negative tokens -1. Alternatively, scores can range from -1 to +1, reflecting the intensity of the sentiment, with +1 representing highly positive sentiment and -1 indicating highly negative sentiment.

In this approach, the sentiment of a given text is determined by aggregating the scores of individual tokens. Each text is divided into tokens, usually single words, and the scores for these tokens are summed separately for positive, negative, and neutral sentiments. The overall sentiment of the text is then determined by comparing these aggregate scores. This method is particularly effective for sentiment analysis at the sentence and feature levels since it does not require labeled training data, qualifying it as an unsupervised technique (Yan-Yan et al., 2010).

However, the lexicon-based approach has significant drawbacks. One major issue is domain dependence, as words can have different meanings in different contexts. For example, the word "small" in "The TV screen is too small" is negative, while in "This camera is extremely small," it is positive because a smaller camera is more portable. This domain-specific nature can lead to inaccuracies if the sentiment lexicon is not tailored to the specific domain being analyzed (Moreo et al., 2012).

To address this issue, developing a domain-specific sentiment lexicon or adapting an existing one is crucial. For instance, the word "huge" can have different sentiments depending on the context: positive in "The queue for the movie was huge" but negative in "There was a huge lag in the network."

The primary advantage of the lexicon-based approach is that it does not require any training data, making it a feasible option for unsupervised sentiment analysis tasks. However, its main disadvantage is its high domain dependency, necessitating careful consideration of context when assigning polarity to words (Wankhade et al., 2022).

2.4.2 Machine Learning Approach

1. **Support Vector Machines (SVM)**: Support Vector Machines are non-probabilistic classifiers that require extensive training datasets. They classify data points using a hyperplane in a (d-1)-dimensional space, aiming to find the hyperplane with the largest possible margin. While highly effective, SVMs are computationally intensive.

2. **N-gram Sentiment Analysis**: This method analyzes contiguous sequences of n items (n-grams) from text or speech, which are collected from a corpus. By utilizing different types of lexicons, it provides a comprehensive analysis of sentiment within the text.

3. **Naïve Bayes Method**: Based on Bayes' theorem, this probabilistic classifier is particularly useful for smaller training datasets. It calculates the probability of a sentiment given a sentence by considering the probabilities of individual tokens, incorporating techniques like Laplace smoothing to handle unseen words.

Calculation as refer to below, the conditional probability that an event X occurs given the evidence Y is determined by Bayes rule by the (1).

P(X/Y) = P(X) P(Y/X) / P(Y) (1)

So for finding the sentiment the equation is transformed into the below (2)

P(Sentiment/Sentence) = P(Sentiment)P(Sentence/Sentiment)/P(Sentence) (2)

P(sentence/sentiment) is calculated as the product of P (token /sentiment), which is formulated by the (3).

Count(Thistokeninclass)+1/Count(Alltokensinclass)+Count(Alltokens) (3)

Here 1 and count of all tokens is called add one or Laplace smoothing.

4. **Maximum Entropy Classifier**: Maximum Entropy classifiers use a set of weights to combine features, operating through an exponential or log-linear model. Unlike other models, they do not assume feature independence and can use Pointwise Mutual Information (PMI) for unsupervised learning to determine word co-occurrences with positive and negative sentiments.

5. **K-Nearest Neighbors (K-NN)**: K-NN classifies instances based on their proximity to neighbors in vector space. The weighted K-NN method enhances this by assigning weights to training set elements, enabling more precise calculation of sentiment scores by considering both positive and negative elements.

   The score is calculated using (4)

   Positivity Score = (1∑j score (pos) + 1∑k score (neg))/ 1∑s maximum score (4)

6. **Multilingual Sentiment Analysis**: Addressing the need for sentiment analysis across multiple languages, this method first identifies the language of the text and then translates it into English using tools such as PROMT. Following translation, sentiment classification is performed.

7. **Feature-Driven Sentiment Analysis**: This approach emphasizes product feature extraction, using structures like the Fuzzy Domain Ontology Sentiment Tree (FDOST) to hierarchically represent products and their features. This method allows for detailed evaluation of sentiments associated with specific product features.

Table 1. Comparison of Different Machine Learning Methods

Methods	Advantages	Disadvantages
1. SVM Method	• Capable of handling high-dimensional input spaces effectively. • Less irrelevant features. • Suitable for sparse document vectors, making it well-suited for text classification tasks.	• Requires a large amount of training data to achieve accurate results. • Data collection process is tedious.
2. N-gram SA	• Utilizing 1-grams and 2-grams as features can significantly improve the accuracy of sentiment prediction compared to using only single-word features.	• Not capturing long-range dependencies in text. • Dependent on having a substantial corpus of training data.
3. Naïve Bayes Method	• A simple and intuitive method that is easy to implement. • It balances efficiency with reasonable accuracy	• Mainly used for small training sets. • Assumes conditional independence among linguistic features, which may not always hold true.

4. Maximum Entropy Classifier	• Does not assume feature independence, unlike the Naïve Bayes method. • Capable of handling large amounts of data effectively.	• Tedious to maintain simplicity of the model.
5. KNN Method	• Considered computationally efficient for certain applications. • Based on the fact that instances nearby it within the vector space are likely to share the same classification	• Requires substantial storage capacity. • Computationally intensive during the recall phase.
6. Multilingual SA	• Capable of evaluate texts in multiple languages without translation. • Capable of handling sentiment analysis across 15 different languages.	• Necessitates a training corpus for each language, which can be resource-intensive to develop.

7. Feature Driven SA	• Adaptable to large projects. • It is a concise process.	• Less effective for smaller projects where the complexity of the approach may not be justified.

Neural Network

Machine learning approaches have significantly advanced the field of sentiment analysis, offering robust methodologies to interpret and classify sentiments in textual data. Among these, Support Vector Machines (SVM), Naïve Bayes, and Maximum Entropy classifiers have been widely used. However, the advent of deep learning has introduced more sophisticated models such as Artificial Neural Networks (ANNs) and Recurrent Neural Networks (RNNs), which have shown superior performance in various applications.

Neural Networks have shown significant promise in sentiment analysis, often outperforming traditional methods in various contexts. Van de Camp and Van den Bosch (2012) demonstrated the use of Neural Networks and Support Vector Machines (SVMs) in identifying supportive relationships through biographical texts, achieving improved results in marking relationships as neutral, positive, or negative. Moraes et al. (2013) conducted a comparative analysis between SVM and Artificial Neural Networks (ANN) in document-level sentiment analysis, highlighting that while SVM is widely used due to its accuracy, ANNs, despite their potential, have received less attention. Their analysis revealed that ANNs generally outperform SVMs, particularly when handling imbalanced data, although they noted the computational cost of training ANNs and the runtime cost of SVMs.

Recurrent Neural Networks (RNNs) are particularly notable for their ability to use previous time step information to predict current time steps, effectively acting as a memory mechanism. However, traditional RNNs suffer from issues like vanishing and exploding gradients, limiting their ability to capture long-term dependencies. Advances like Bi-directional Long Short-Term Memory (Bi-LSTM) networks address these limitations by processing information in both forward and backward directions, enhancing their capability to understand context in sentiment analysis.

Attention models and recent advancements in transfer learning, such as BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre-trained Transformer), have further revolutionized the field. These models, pretrained on massive corpora, can be fine-tuned with specific datasets to achieve high accuracy in sentiment analysis. The introduction of the Transformer model by Vaswani et al. (2017) marked a significant breakthrough, utilizing self-attention and multi-headed attention mechanisms to process input data more effectively and in parallel, leading to superior performance in NLP tasks.

Deep learning techniques, including CNN-RNN hybrids and attention-based models, have been extensively employed in sentiment analysis, demonstrating outstanding performance in capturing both long-term dependencies and local features. These models have been applied successfully across various languages and domains, indicating their versatility and robustness.

2.5 Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) in Sentiment Analysis

2.5.1 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a type of deep learning model particularly well-suited for image recognition and text classification tasks. In the context of sentiment analysis, CNNs are used to capture local patterns in text data by applying convolutional filters over input sequences, which allows them to identify phrases or combinations of words indicative of sentiment.

Advantages of CNNs:

1. **Efficient Feature Extraction:** CNNs are highly efficient at extracting features from text data, making them particularly effective for identifying significant phrases or n-grams that convey sentiment.
2. **Parallel Processing:** CNNs can process multiple parts of the text simultaneously, leading to faster computation times compared to sequential models like RNNs.
3. **Hierarchical Pattern Recognition:** CNNs can capture hierarchical structures in text, which is useful for understanding complex sentiment expressions.

Applications in Sentiment Analysis: CNNs have been effectively applied to sentiment analysis, achieving high accuracy in classifying sentiments in texts like tweets or reviews. They are particularly useful for short texts where local dependencies are crucial (Kim, 2014; Kalchbrenner et al., 2014). For instance, in a study by Abdulfatir, various CNN architectures were used to analyze tweets, showing significant improvements in accuracy with each successive model layer (Abdulfatir, 2021).

2.5.2 Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNNs) are designed to handle sequential data by maintaining a hidden state that captures information from previous steps in the sequence. This makes RNNs suitable for tasks where the order of words is essential, such as language modeling and sequence prediction.

Advantages of RNNs:

1. **Sequential Data Handling:** RNNs are inherently designed to process sequences, making them ideal for understanding the context provided by previous words.
2. **Contextual Information:** By maintaining a hidden state, RNNs can capture long-term dependencies, which are crucial for tasks requiring an understanding of context over longer text spans.

Challenges with RNNs:

1. **Vanishing/Exploding Gradients:** Traditional RNNs struggle with long-term dependencies due to vanishing or exploding gradient issues, which can hinder learning.
2. **Computational Intensity:** RNNs can be computationally intensive due to their sequential processing nature, which limits parallelism.

Improvements with LSTM and GRU: LSTM networks and GRUs address some limitations of traditional RNNs by introducing mechanisms to retain long-term dependencies and manage information flow more effectively (Hochreiter & Schmidhuber, 1997; Cho et al., 2014).

Applications in Sentiment Analysis: RNNs, LSTMs, and GRUs are widely used for sentiment analysis, especially for longer texts like reviews and articles, where the sentiment is spread across multiple sentences (Liu et al., 2016; Pham & Le-Hong, 2017). In a study by Abdulfatir, LSTM models were used for sentiment analysis on tweets, showing promising results with different configurations and embeddings (Abdulfatir, 2021).

2.6 Choosing Between CNN and RNN for Sentiment Analysis in Mental Health Applications

In the study conducted by Abdulfatir (2021), an ensemble model was developed to enhance the accuracy of sentiment analysis on tweets. The approach involved extracting 600-dimensional feature vectors from each tweet using the penultimate layer of a high-performing 4-Conv-NN model. These feature vectors were subsequently classified using a linear Support Vector Machine (SVM) with a regularization parameter of C=1. The ensemble model combined the predictions from five different models through majority voting, which included LSTM-NN, 4-Conv-NN, 4-Conv-NN features + SVM, 4-Conv-NN with max_length = 20, and 3-Conv-NN.

Summary of Achievements: The dataset comprised tweets containing a mix of words, emoticons, URLs, hashtags, user mentions, and symbols. The data underwent preprocessing to ensure suitability for model training. Several machine learning algorithms were implemented, including Naive Bayes, Maximum Entropy, Decision Tree, Random Forest, XGBoost, SVM, Multi-Layer Perceptron, Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs), to classify the sentiment polarity of the tweets.

Two types of features, unigrams and bigrams, were used for classification. It was observed that augmenting the feature vector with bigrams improved accuracy. Feature representation was achieved using both sparse and dense vectors, with sparse vector representation demonstrating superior performance compared to frequency-based methods.

Neural network methods generally outperformed other classifiers. The best LSTM model achieved an accuracy of 83.0% on the Kaggle leaderboard, while the best CNN model reached an accuracy of 83.34%. Furthermore, the model that combined features from the best CNN model and classified them using SVM performed slightly better than the standalone

CNN. Ultimately, the ensemble method, which took a majority vote over the predictions of the top five models, achieved the highest accuracy of 83.58%.

This comprehensive approach underscores the effectiveness of combining multiple models and methodologies to enhance sentiment analysis performance, particularly in the context of varied and complex datasets like Twitter.

Why Choose CNN Over RNN:

1. **Efficiency with Short Texts:** For mental health applications, where data sources include short texts like tweets, comments, or forum posts, CNNs are more efficient due to their ability to capture local dependencies quickly.
2. **Computational Efficiency:** CNNs require less computational power compared to RNNs as they can leverage parallel processing, making them suitable for real-time applications and large datasets.
3. **Effective Feature Extraction:** CNNs' ability to extract hierarchical patterns and features from text can be beneficial for identifying nuanced sentiment expressions in mental health discussions.

However, for tasks involving longer texts where the context is spread out over multiple sentences or paragraphs, RNNs (specifically LSTMs or GRUs) may still be necessary to capture the overall sentiment accurately. Combining CNNs and RNNs can leverage the strengths of both models. CNNs can handle feature extraction and local pattern recognition, while RNNs can capture sequential dependencies and context, offering a comprehensive approach to sentiment analysis (Wang et al., 2016).

For instance, In the study conducted by Abdulfatir (2021), an ensemble model was developed to enhance the accuracy of sentiment analysis on tweets. The approach involved extracting 600-dimensional feature vectors from each tweet using the penultimate layer of a high-performing 4-Conv-NN model. These feature vectors were subsequently classified using a linear Support Vector Machine (SVM) with a regularization parameter of C=1. The ensemble model combined the predictions from five different models through majority voting, which included LSTM-NN, 4-Conv-NN, 4-Conv-NN features + SVM, 4-Conv-NN with max_length = 20, and 3-Conv-NN.

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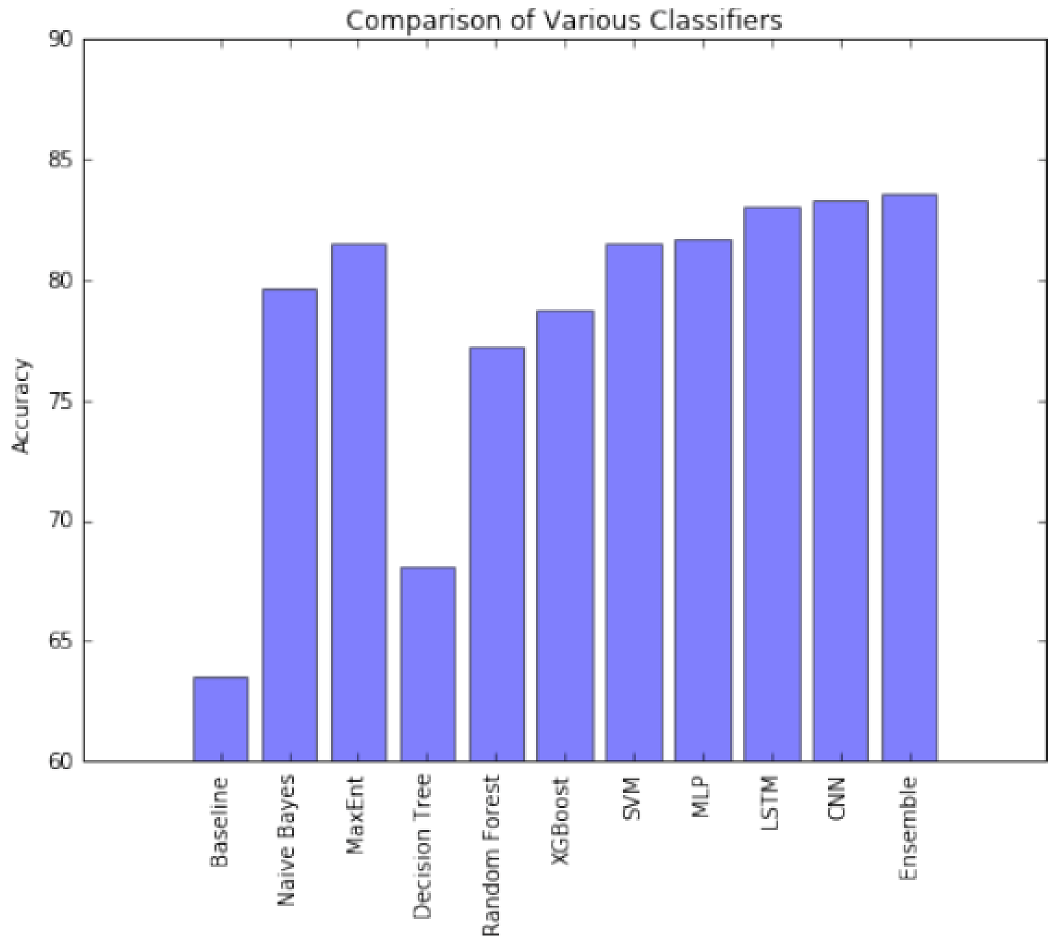
Figure from Abdulfatir, M. (2021)



This comprehensive approach underscores the effectiveness of combining multiple models and methodologies to enhance sentiment analysis performance, particularly in the context of varied and complex datasets like Twitter.

Hybrid Approach

The hybrid approach in sentiment analysis merges machine learning techniques with lexicon-based methods. This combined strategy leverages the strengths of both methodologies, making it highly popular in the field. Sentiment lexicons are crucial components in many hybrid systems. For instance, Hassonah et al. (2020a) developed a hybrid machine learning model using Support Vector Machine (SVM) and two feature selection techniques: the multi-verse optimizer and Relief algorithms. This approach aimed to enhance sentiment analysis accuracy.

Another study by Al Amrani et al. (2018) proposed a hybrid model combining Random Forest (RF) and SVM. Their results showed that while individual models of SVM and RF achieved accuracies of 81.01% and 82.03% respectively, the hybrid model reached nearly 84% accuracy on an Amazon product review dataset. This demonstrates the potential of hybrid models to outperform individual machine learning algorithms.

Moreover, Hassonah et al. (2020b) utilized Twitter data, extracting around 6,900 tweets for training their hybrid model. Their findings indicated that the hybrid model outperformed many existing models while reducing the number of features by up to 96%. They emphasized the potential of hybrid models, suggesting that with appropriate architecture and fine-tuning of hyperparameters, these models can surpass the performance of standalone models.

In summary, hybrid approaches combining lexicon-based and machine learning techniques are promising for sentiment analysis. They leverage the advantages of both methods, offering improved performance and reduced feature complexity. However, there remains significant potential for further research and optimization to fully realize the benefits of hybrid models (Chang et al., 2020).

Table 2: Comparison between sentiment classification approaches by (Alessia et al., 2015).

Sentiment Classification Approaches	Features/Techniques	Advantages	Limitations
Lexicon Based	• Manual construction • Corpus-based • Dictionary-based	• Broader term coverage.	• Finite number of words in the lexicons and fixed sentiment orientation and scores for words.
Machine Learning	• Term presence and frequency	• Capable of adapting and	• Limited applicability to new

	• Part of speech information • Negations • Opinion words and phrases	creating trained models tailored for specific purposes and contexts. .	data due to the necessity of labeled data, which can be costly or prohibitive to obtain.
Hybrid	• Combines Machine Learning and Lexicon-based approaches • Sentiment lexicon constructed using public resources for initial sentiment detection. • Sentiment words used as features in machine learning methods.	• Symbiotic use of lexicon and learning methods, effective sentiment detection at the concept level, and less sensitivity to changes in topic domain.	• Susceptible to noisy reviews.

2.7 Conclusion

In mental health applications, the hybrid approach stands out as the most appropriate for sentiment analysis. This method integrates the benefits of both lexicon-based and machine learning techniques, resulting in enhanced performance and simplified feature complexity. Lexicon-based approaches are particularly useful due to their unsupervised nature and their effectiveness at both sentence and feature levels. However, these methods are often limited by their domain dependence, leading to potential inaccuracies across different contexts (Kiritchenko et al., 2014; Moreo et al., 2012).

On the other hand, machine learning techniques such as Support Vector Machines (SVM), Naïve Bayes, and Maximum Entropy Classifiers offer strong classification capabilities but usually necessitate extensive training datasets and can be computationally demanding (Wankhade et al., 2022). The hybrid approach mitigates these issues by incorporating sentiment lexicons with machine learning techniques, thereby achieving higher accuracy and efficiency.

Research has demonstrated that hybrid models, such as those combining SVM with Random Forest or utilizing sophisticated feature selection algorithms, outperform individual machine learning models, making them particularly effective for detailed sentiment analysis in the mental health field (Al Amrani et al., 2018; Hassonah et al., 2020a, 2020b). Consequently, for mental health applications, where the context and precise detection of sentiment are critical, the hybrid approach proves to be the most promising solution.

2.7 Challenges of Sentiment Analysis

In this digital era, the vast amount of informal text generated on social media platforms presents substantial challenges for sentiment and emotion analysis. The presence of spelling mistakes, new slang, and incorrect grammar complicates the process for machines to accurately interpret emotions. For instance, the sentence “Y have u been soooo late?” contains misspellings and exaggerated words, making it difficult to discern whether the speaker is expressing anger or worry (Batbaatar et al., 2019).

A significant challenge in emotion recognition and sentiment analysis is the scarcity of resources. Although data collection is relatively straightforward, the manual annotation of large datasets is both time-consuming and often unreliable (Balahur & Turchi, 2014). Moreover, most resources are predominantly in English, posing difficulties for analyzing text in other languages, particularly regional ones. The domain-specific nature of many corpora and lexicons further limits their broader applicability.

Web slang is another considerable obstacle. Terms like 'LOL' (laughing out loud) and 'FOMO' (fear of missing out) expand the vocabulary that existing lexicons and models need to understand. Detecting sarcasm and irony also presents significant challenges, as these expressions can obscure the true sentiment. For example, the sentence “This story is excellent to put you to sleep” employs sarcasm, using the word 'excellent' to indicate boredom rather than approval (Ghanbari-Adivi & Mosleh, 2019).

Additionally, sentences expressing multiple emotions present further complications. For instance, the sentence “The view at this site is so serene and calm, but this place stinks” conveys both 'soothing' and 'disgust' emotions. Determining sentiment polarity from comparative sentences is equally complex. Sentences like “Phone A is worse than Phone B” and “Phone B is worse than Phone A” both use the term 'worse' negatively, yet they convey opposite sentiments (Shelke, 2014).

These complexities underscore the ongoing challenges and opportunities in the field of sentiment and emotion detection from real-world data (Nandwani & Verma, 2021).

Methodological Challenges

Wankhade et al. (2022) stated that Sentiment analysis faces several methodological challenges. One significant challenge is the detection of ambiguity and sarcasm. Sarcastic remarks often convey sentiments that are opposite to the literal meaning of the words, posing a significant challenge to conventional sentiment analysis models (Castro et al., 2019; Medhat et al., 2014; Poria et al., 2018a). Furthermore, the integration of multimodal data, such as text, audio, and video, can enhance sentiment analysis accuracy. For instance, combining vocal and facial expressions with textual data can improve the detection of sarcasm (Poria et al., 2018a; McDuff et al., 2014).

Informal Writing Style

The informal writing style prevalent on social media, characterized by the use of acronyms, emojis, and slang, complicates sentiment analysis. Additionally, grammatical errors and spelling mistakes are common in such texts, requiring constant updates to models and lexicons to maintain accuracy. These informal elements evolve rapidly, necessitating continuous adaptation.

Computational Cost

Advanced sentiment analysis models, particularly neural networks, come with high computational costs. Training these models on large datasets demands substantial computational resources, including high-end GPUs, which can be prohibitively expensive.

Availability and Quality of Data

Although data for sentiment analysis is plentiful, high-quality annotated datasets are scarce. This scarcity is especially evident in domain-specific data, which often necessitates manual annotation. This process is both time-consuming and costly, hindering the development of accurate models.

Language Adaptations and Variability

Language variations across different regions and the evolution of slang present significant challenges for sentiment analysis. Words can have different meanings in different regions, affecting model accuracy. Furthermore, most sentiment analysis resources are available in English, making it difficult to analyze texts in other languages.

Degree Adverbs and Intensifiers

Degree adverbs and intensifiers, such as "barely" or "really," play a critical role in quantifying sentiment. These modifiers can complicate the aggregation and comparison of sentiment values, necessitating precise interpretation for accurate sentiment analysis.

Mixed Code Data

Code-mixing, or the use of multiple languages within a single sentence, is common in multilingual societies and poses a significant challenge for sentiment analysis. The absence of formal grammar for code-mixed phrases complicates analysis, requiring new language models to handle this phenomenon effectively (Pravalika et al., 2017; Poria et al., 2020; Vijay et al., 2018; Chatterjere et al., 2020).

The challenges in sentiment analysis are multifaceted, involving issues related to the structure and nature of sentiments, methodological approaches, data quality, language variability, and computational costs. Addressing these challenges requires ongoing research and the development of advanced techniques to enhance the accuracy and applicability of sentiment analysis across diverse contexts (Wankhade et al., 2022).

Advantages of Sentiment Analysis Web Applications to User

Sentiment analysis web applications offer numerous benefits to users, particularly in the context of mental health. These applications leverage natural language processing and machine learning to analyze textual data, providing insights that can significantly impact individuals and communities. Here are some key advantages:

1. Early Detection of Mental Health Issues

One of the primary benefits of sentiment analysis web applications is their ability to detect early signs of mental health issues. By analyzing posts, comments, and other textual data on social media platforms and forums, these applications can identify negative sentiments and emotional distress that may indicate conditions such as depression, anxiety, or bipolar disorder. This early detection can prompt timely interventions and support, potentially preventing the escalation of mental health problems (Calvo, Milne, Hussain, & Christensen, 2017).

2. Anonymity and Accessibility

Sentiment analysis applications provide users with an anonymous platform to express their emotions and seek support. This anonymity can be crucial for individuals who are reluctant to seek help due to the stigma associated with mental health issues. Online platforms can reach a broader audience, including those in remote or underserved areas, offering a level of accessibility that traditional mental health services may lack (Naslund, Aschbrenner, Marsch, & Bartels, 2016).

3. Real-Time Monitoring and Feedback

These applications offer real-time monitoring of users' emotional states, providing immediate feedback and support. For instance, if a user's sentiment analysis indicates severe distress, the application can automatically offer resources, coping strategies, or contact information for mental health professionals. This real-time capability ensures that individuals receive timely assistance when they need it most (De Choudhury, Counts, & Horvitz, 2013).

4. Personalized Mental Health Insights

Sentiment analysis web applications can deliver personalized insights into users' mental health over time. By tracking changes in sentiment and emotional expression, these applications help users understand patterns in their mood and behavior. This self-awareness can empower individuals to take proactive steps in managing their mental health and seeking professional help when necessary (Trotzek, Schroeder, & Stein, 2018).

5. Data-Driven Decision Making for Mental Health Professionals

For mental health professionals, sentiment analysis applications provide valuable data-driven insights that can inform treatment plans and interventions. By analyzing aggregated data from multiple users, professionals can identify trends, common triggers, and effective coping strategies. This information can enhance the quality of care provided and support the development of targeted mental health programs (Ireland & Penn, 2017).

6. Community Support and Engagement

These applications facilitate community support and engagement by connecting individuals with similar experiences. Online forums and support groups analyzed through sentiment analysis can create a sense of belonging and mutual support, which is crucial for individuals dealing with mental health challenges. Sharing experiences and receiving validation from peers can significantly improve mental well-being (Barak, Boniel-Nissim, & Suler, 2008).

In conclusion, sentiment analysis web applications provide significant advantages for users, including early detection of mental health issues, anonymity and accessibility, real-time monitoring, personalized insights, data-driven decision-making, and enhanced community support. These benefits highlight the potential of technology to transform mental health care and support systems, making them more responsive, personalized, and inclusive.

3.0 Methodology for Sentiment Analysis Mental Health Application

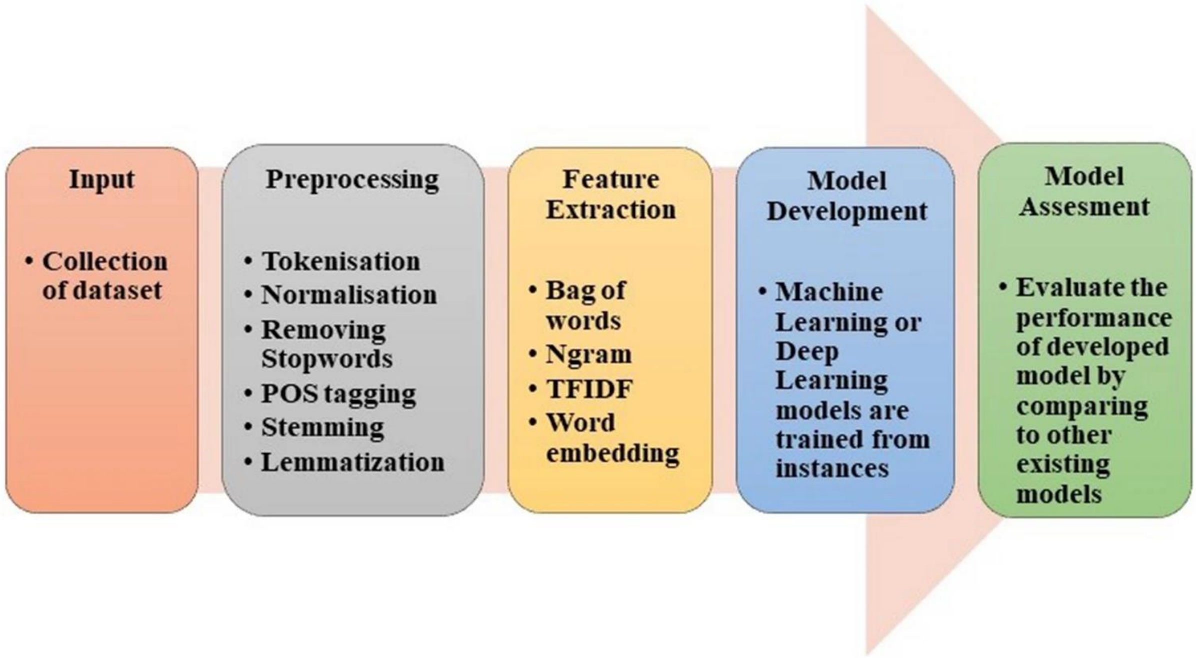
3.1 Tools to be Used in this Methodology

1. **Programming Language:**

    - Python
2. **Web Framework:**
    - **Backend:** Flask or Django
    - **Frontend:** HTML, CSS, and JavaScript with frontend frameworks like React.js or Angular
3. **Database:**
    - PostgreSQL or MongoDB
4. **Machine Learning Libraries:**
    - Scikit-learn, TensorFlow, Keras, NLTK, SpaCy
5. **Text Processing Libraries:**
    - NLTK, SpaCy, TextBlob
6. **Visualization Libraries:**
    - Matplotlib, Seaborn
7. **Deployment Platform:**
    - AWS (Amazon Web Services), Heroku, Google Cloud Platform
8. **Version Control and Collaboration:**
    - GitHub
9. **API for Data Extraction:**
    - Twitter API as well as Tweepy Library, Reddit API
10. **Word Embedding Models:**
    - GloVe (Global Vectors for Word Representation), Word2Vec
11. **Sentiment Analysis Tools:**
    - VADER (Valence Aware Dictionary and sEntiment Reasoner)
12. **Development Environment:**
    - Jupyter Notebook, Spyder, Visual Studio Code

3.2 Language/Framework/Model Requirements

The sentiment analysis application for mental health will be developed using Python, chosen for its comprehensive libraries and simplicity in data analysis and machine learning. The backend of the web application will be managed using Django, a robust framework for server-side operations. The frontend will be built using HTML, CSS, and JavaScript, supplemented with modern frameworks such as React.js to ensure a dynamic and responsive user interface. For data storage and retrieval, PostgreSQL will be utilized due to its efficiency and scalability. The application will leverage various machine learning libraries, including Scikit-learn, TensorFlow, Keras, NLTK, and SpaCy for building and training models. Text processing will be handled using NLTK, SpaCy, and TextBlob to preprocess and analyze text data effectively. Visualization of data and results will be facilitated by Matplotlib and Seaborn. Finally, the application will be deployed on cloud platforms such as AWS, Heroku, or Google Cloud Platform to ensure scalability and accessibility.



Img 2: An example of sentiment analysis process by (Nandwani & Verma, 2021).

3.3 Data Collection

Data collection is the foundational step in our sentiment analysis application. We will gather a diverse and representative dataset relevant to mental health from various online sources:

1. **Social Media Data**: Extract posts and comments from platforms like Twitter and Reddit. Specifically, subreddits like r/mentalhealth, r/depression, r/anxiety, r/bipolar, and r/SuicideWatch provide valuable data (Reddit API, Twitter API). The GitHub repository by Gkotsis et al. (2021) provides an excellent starting point for extracting and preprocessing data from Reddit.
    - **Twitter**: The Tweepy library will be used to interact with the Twitter API to collect tweets based on specific hashtags like #MentalHealth, #Depression, #Anxiety, and #MentalHealthAwareness.

    - **Reddit**: Data will be collected from subreddits such as r/mentalhealth, r/depression, r/anxiety, and r/SuicideWatch using the PRAW (Python Reddit API Wrapper) library.
2. **Clinical Data (Optional to collect)** Anonymized transcripts from therapy sessions or mental health support groups will be collected, ensuring ethical guidelines and privacy regulations are strictly followed.

3.4 Data Preprocessing

Text preprocessing involves transforming raw text data into a structured and clean format suitable for analysis. This step is crucial for improving the efficiency and effectiveness of various NLP tasks, including sentiment analysis. Text preprocessing typically includes several key tasks: tokenization, normalization, removing stop words, part-of-speech (POS) tagging, stemming, and lemmatization (Manning et al., 2008).

Text Cleaning

Removing HTML tags, special characters, URLs, and other non-textual elements using libraries such as BeautifulSoup and re (regular expressions).

Normalization

Normalization is a crucial step in data preprocessing, ensuring that text data is in a consistent format, making it easier to analyze and compare. This process involves several sub-steps. Firstly, converting all characters in the text to lowercase ensures that words like "Text" and "text" are treated as the same word, eliminating case sensitivity issues. Secondly, punctuation marks are removed to prevent them from being treated as separate tokens, thus simplifying the tokenization process. Thirdly, handling special characters involves removing or replacing non-alphanumeric characters, ensuring that only meaningful text is analyzed. Lastly, removing extra spaces ensures consistent tokenization, as unnecessary spaces can lead to incorrect parsing of the text.

Tokenization

Tokenization is the process of splitting text into smaller units called tokens, which are typically words or phrases. It converts a stream of text into individual elements that can be analyzed. For instance, the sentence "The quick brown fox jumps over the lazy dog" can be

tokenized into ["The", "quick", "brown", "fox", "jumps", "over", "the", "lazy", "dog"] (Manning, Raghavan, & Schütze, 2008).
Python libraries such as NLTK or SpaCy can be used for Splitting text into individual tokens (words or phrases).

Stop Word Removal

Stop words are common words such as "and", "the", "is", and "in" that often do not carry significant meaning and can be removed to reduce the dimensionality of the text data. Removing these words helps in focusing on the meaningful words that contribute to sentiment analysis (Manning, Raghavan, & Schütze, 2008).
For instance, eliminating common words that do not contribute meaningful information using NLTK's stopwords list.

POS Tagging

POS tagging is also an essential component of data preprocessing. By labeling each word with its corresponding part of speech, such as nouns, verbs, or adjectives, it helps in understanding the syntactic structure of the text. This can improve the accuracy of sentiment analysis by identifying the role each word plays in a sentence. Including POS tagging in the preprocessing phase adds a layer of depth to the analysis, enabling more nuanced understanding of the text.

Lemmatization and Stemming

Lemmatization also reduces words to their base or dictionary form but considers the context of the word to ensure an accurate base form. For example, "running" would be lemmatized to "run" and "better" to "good". Lemmatization is often more accurate than stemming as it takes into account the part of speech and meaning of the word (Manning, Raghavan, & Schütze, 2008).
Reducing words to their base or root forms using NLTK and SpaCy to standardize the text.

Feature Extraction

Feature extraction transforms text data into numerical representations for machine learning models:

1. **Bag of Words (BoW)**: Represents text as a collection of word frequencies.
2. **Term Frequency-Inverse Document Frequency (TF-IDF)**: This technique weighs the importance of words based on their frequency and rarity in the document, using Scikit-learn's TfidfVectorizer.
3. **Word Embeddings**: Dense vector representations like Word2Vec, GloVe, and FastText are used to capture semantic relationships between words. GloVe embeddings, provided by the Stanford NLP Group, will be particularly useful.

3.5 Model Selection and Training

For our sentiment analysis model, we will use a hybrid approach, combining lexicon-based methods with machine learning techniques to leverage the strengths of both methodologies. This hybrid approach is selected because it offers the robustness of machine learning models in capturing complex patterns in data and the interpretability of lexicon-based methods.

The hybrid approach is selected for its balanced advantage of combining interpretability and accuracy. Lexicon-based methods, such as VADER, offer straightforward sentiment scores that are easy to interpret, making them ideal for initial sentiment classification. On the other hand, machine learning models, particularly deep learning models like CNNs and RNNs, are adept at capturing complex patterns in text data, thereby enhancing the accuracy and robustness of the sentiment analysis. This combination ensures that the model can handle a wide range of contexts and datasets, making it more versatile and effective for mental health applications.

Lexicon-Based Sentiment Analysis (VADER)

VADER (Valence Aware Dictionary and sEntiment Reasoner) is a lexicon and rule-based sentiment analysis tool specifically attuned to sentiments expressed in social media. It provides initial sentiment scores that serve as features for machine learning models (Hutto & Gilbert, 2014). VADER will be integrated using the `vaderSentiment` library in Python, with NLTK for text preprocessing tasks such as tokenization and stopword removal.

Machine Learning Models

Support Vector Machines (SVM): SVMs are effective for high-dimensional spaces and are used to classify sentiment based on features extracted from the text data. They will serve as one component of our ensemble approach due to their robustness and effectiveness in text classification.

Convolutional Neural Networks (CNNs): CNNs are chosen for their ability to capture local dependencies in text data. Implemented using TensorFlow and Keras, the CNN architecture will include embedding layers initialized with GloVe vectors, multiple convolutional layers with ReLU activation, pooling layers, fully connected layers, and dropout for regularization (Kim, 2014).

Recurrent Neural Networks (RNNs): Specifically, Long Short-Term Memory (LSTM) networks will be used to capture long-term dependencies in the text data. RNNs will also be implemented using TensorFlow and Keras, with LSTM layers following the embedding layer and including dropout for regularization (Hochreiter & Schmidhuber, 1997).

Hybrid Models

To further improve accuracy, an ensemble model will be created by combining predictions from multiple models, such as CNN, LSTM, and SVM, using majority voting (Abdulfatir, 2021). This ensemble approach leverages the strengths of different models, resulting in a more robust and accurate sentiment analysis.

For deep learning models, the implementation involves using libraries like TensorFlow and Keras. Training involves splitting the dataset into training and validation sets and optimizing the models to minimize prediction errors. For example, the CNN model implementation can follow the architecture detailed by Abdulfatir (2021) using TensorFlow, with embedding layers initialized with GloVe vectors and Adam optimizer for training. Similarly, RNNs with LSTM layers can be initialized with GloVe vectors, fine-tuned during training, and optimized using the Adam optimizer (Abdulfatir, 2021).

Hutto, C.J. & Gilbert, E.E. (2014). VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text. Eighth International Conference on Weblogs and Social Media (ICWSM-14). Ann Arbor, MI, June 2014.

Model Evaluation

Model performance will be evaluated using various metrics to ensure they accurately predict sentiment. Here's how to implement these evaluations:

1. **Accuracy**: Measure the proportion of correctly classified instances among the total instances. Use Scikit-learn's `accuracy_score` function.
2. **Precision, Recall, and F1 Score**: Precision measures the number of true positive results divided by the number of all positive results. Recall measures the number of true positive results divided by the number of positives that should have been retrieved. F1 Score is the harmonic mean of precision and recall. Use Scikit-learn's `classification_report` function.
3. **Confusion Matrix**: Visualize the performance of the classification model by showing the correct and incorrect classifications for each sentiment class. Use Scikit-learn's `confusion_matrix` and `ConfusionMatrixDisplay` functions.

Web Application

The model is integrated into a web framework such as Flask or Django, enabling it to process incoming text data and generate sentiment predictions. The user interface is developed using HTML, CSS, and JavaScript, along with frontend frameworks like React.js or Angular, to create an intuitive and interactive experience.

3.6 Requirement Analysis

3.1.1 Functional and Non-Functional Requirements for User

Functional Requirements

FR1.1: The system shall allow the user to create an account and log in using their email and password.

FR1.2: The system shall provide a user-friendly interface for users to input text related to their mental health.

FR1.3: The system shall perform sentiment analysis on the input text to determine the user's mental health condition.

FR1.4: The system shall provide feedback and advice based on the results of the sentiment analysis.

FR1.5: The system shall allow users to export or download their feedback and evaluation results in formats such as PDF or CSV.

Non-Functional Requirements

NFR1.1 (Security): The system shall ensure that only authorized users can access their data to maintain confidentiality and privacy.

NFR1.2 (Usability): The system should be easy to use, with users being able to navigate and utilize its functionalities effectively within five minutes of learning.

NFR1.3 (Performance): The system should perform sentiment analysis and provide feedback in real-time or within a few seconds to ensure a smooth user experience.

NFR1.4 (Scalability): The system should be able to handle a growing number of users and increasing amounts of input data without performance degradation.

NFR1.5 (Reliability): The system should maintain high availability and reliability, ensuring users can access their data and receive feedback whenever needed.

3.1.2 Functional and Non-Functional Requirements for Administrator

Functional Requirements

FR2.1: The system shall allow the administrator to log in using a secure ID and password.

FR2.2: The system shall allow the administrator to manage user accounts, including creating, updating, and deleting accounts.

FR2.3: The system shall allow the administrator to monitor system performance and user activity for maintenance and security purposes.

FR2.4: The system shall enable the administrator to update the sentiment analysis model and underlying lexicons as needed.

FR2.5: The system shall provide the administrator with tools to generate reports on system usage and user feedback data.

Non-Functional Requirements

NFR2.1 (Security): The system shall restrict access to administrative functions to authorized personnel only, ensuring robust security measures are in place.

NFR2.2 (Usability): The administrative interface should be intuitive and easy to navigate, allowing administrators to perform their tasks efficiently.

NFR2.3 (Modifiability): The system should allow the administrator to implement changes to user accounts and system settings quickly and with minimal effort.

NFR2.4 (Maintainability): The system should be designed for easy maintenance, with clear documentation and support for troubleshooting common issues.

3.1.3 Functional and Non-Functional Requirements for Sentiment Analysis Model

Functional Requirements

FR3.1: The system shall utilize a hybrid approach for sentiment analysis, combining lexicon-based methods with machine learning techniques.

FR3.2: The system shall preprocess user input text by normalizing, tokenizing, and removing stop words.

FR3.3: The system shall use the VADER tool for initial sentiment scoring.

FR3.4: The system shall employ Convolutional Neural Networks (CNNs) for feature extraction from the text data.

FR3.5: The system shall use Recurrent Neural Networks (RNNs), specifically LSTM networks, to capture long-term dependencies in the text data.

FR3.6: The system shall integrate ensemble models to improve accuracy by combining predictions from multiple models.

Non-Functional Requirements

NFR3.1 (Performance): The sentiment analysis model should process text inputs and generate results within a few seconds.

NFR3.2 (Scalability): The model should handle an increasing volume of data and user inputs without significant performance loss.

NFR3.3 (Accuracy): The model should achieve high accuracy in sentiment classification to provide reliable feedback to users.

NFR3.4 (Adaptability): The model should be adaptable to incorporate new data and improve over time with continuous learning mechanisms.

Use Cases Descriptions

Use Case: User Registration and Login

Actors: User

Description: This use case describes the process by which a new user creates an account on the platform and subsequently logs in.

Process:

The user navigates to the registration page.

The user enters their email and creates a password.

The system verifies the email's uniqueness and strength of the password.

The system stores the user's credentials securely.

The user receives a confirmation email and verifies their account.

The user logs in by entering their email and password on the login page.

The system authenticates the user and grants access to the platform.

Use Case: Text Input and Sentiment Analysis

Actors: User

Description: This use case details how users input text related to their mental health and receive sentiment analysis feedback.

Process:

The user logs into their account.

The user navigates to the text input section.

The user enters their text regarding their mental health condition.

The system preprocesses the text (normalization, tokenization, removal of stop words).

The system performs sentiment analysis using the hybrid model.

The system displays the sentiment analysis results and feedback to the user.

Use Case: Export Feedback

Description: This use case details how users input text related to their mental health and receive sentiment analysis feedback.

Actors: User

Description: This use case explains how users can export their sentiment analysis feedback.

Process:

The user views their sentiment analysis results.

The user selects the export option.

The system prompts the user to choose the desired format (e.g., PDF, CSV).

The system generates the file and provides a download link to the user.

Use Case: Manage User Accounts

Actor: Administrator

Description: This use case covers how an administrator manages user accounts.

Process:

The administrator logs into the admin panel.

The administrator views a list of user accounts.

The administrator can create, update, or delete user accounts.

The system processes the changes and updates the database accordingly.

Activity Descriptions

Activity: Preprocessing User Input

Description: This activity involves preparing the raw text input from users for sentiment analysis.

Process:

Normalization: Convert all text to lowercase, remove punctuation, handle special characters, and remove extra spaces.

Tokenization: Split the text into individual tokens or words.

Stop Word Removal: Remove common words that do not contribute significantly to the sentiment analysis.

Lemmatization/Stemming: Reduce words to their base or root forms to standardize the text.

Activity: Performing Sentiment Analysis

Description: This activity describes the process of analyzing the preprocessed text to determine sentiment.

Process:

Lexicon-Based Analysis: Use VADER to provide initial sentiment scores.

Feature Extraction with CNNs: Apply Convolutional Neural Networks to capture local dependencies in the text.

Long-Term Dependencies with RNNs: Use LSTM networks to capture long-term dependencies.

Combining Results: Integrate results from both models and use ensemble techniques to improve accuracy.

Generating Feedback: Produce a sentiment score and corresponding feedback based on the analysis.

Activity: Exporting Feedback

Description: This activity involves providing the user with an option to download their analysis results.

Process:

Format Selection: Allow the user to choose the desired export format.

File Generation: Generate the feedback file in the selected format.

Download Provision: Provide the user with a download link for the generated file.

Entity Relationship Descriptions

Entity: User

- **Attributes:** UserID, Email, Password, RegistrationDate
- **Relationships:** Each user can input multiple texts and receive multiple feedbacks.

Entity: TextInput

- **Attributes:** TextID, UserID, InputText, DateSubmitted
- **Relationships:** Each text input is associated with a single user and can generate multiple analysis results.

Entity: SentimentAnalysis

- **Attributes:** AnalysisID, TextID, SentimentScore, Feedback, AnalysisDate
- **Relationships:** Each sentiment analysis is linked to a specific text input and provides one set of results.

Entity: Feedback

- **Attributes:** FeedbackID, AnalysisID, FeedbackText, Exported
- **Relationships:** Each feedback entry is connected to a sentiment analysis and can be exported by the user.

Visualization and Interpretation

Visualizing the results of sentiment analysis significantly enhances interpretation and understanding. Using libraries such as Matplotlib and Seaborn, we will generate visual representations that depict sentiment distribution and trends within the data. Additionally, we will develop interactive dashboards to present these analysis results in a user-friendly format, enabling real-time insights and facilitating a deeper understanding of the sentiment landscape. These visualization tools will provide a clear and intuitive way to explore and interpret the findings from the sentiment analysis.

4.0 Work Plan and Timeline

4.1 Work Plan

Project Planning (2 weeks)

Work/Activities	Description	Deliverables	Risk Factors	Duration
Initiate Research on Topic	Conduct a general search	A draft of the initial project	The background of the project	1 day

	by browsing the web to gather information about the project title. All relevant information will be documented to consolidate understanding of the project.	plan that includes background information on the project title.	title could be underestimated due to overlooking certain details when searching for information.	
Identify the Problem Statement	Develop a precise problem statement based on the comprehensive background research. This statement will clearly articulate the specific issue the project aims to address and its significance.	A well-defined problem statement that outlines the project's primary issue and proposed solution.	Misidentifying the core problem due to incomplete understanding may lead to an ineffective project focus.	4 days
Define Project Objectives and Scope	Establish the project's objectives and scope to ensure a focused and	Clearly defined project objectives and scope to guide the project	The objectives and scope may be overly ambitious, risking	3 days

	achievable approach. The objectives will specify what the project aims to accomplish, while the scope will delineate the boundaries of the project's coverage.	direction and prevent scope creep.	unachievable goals within the given time constraints.	
Plan Project Activities and Schedule	Develop a detailed work plan and timeline for the project, encompassing all necessary activities and their respective durations. This includes creating a Gantt chart to visualize the schedule and highlight dependencies.	A comprehensive work plan and Gantt chart illustrating all activities, their dependencies, and timelines.	The accuracy of estimated activity durations might be challenged, requiring adjustments as the project progresses.	1 week

Requirements Engineering (5 Weeks)

Work/Activities	Description	Deliverables	Risk Factors	Duration
Conduct Literature Review	Perform an extensive review of relevant literature, focusing on journal articles and existing systems related to sentiment analysis and mental health. Careful selection and examination of credible sources will ensure the review's relevance.	An in-depth literature review providing insights into existing sentiment analysis methods.	Difficulty in finding relevant and credible sources may extend the research time needed.	3 weeks
Identify Gaps in Literature	Analyze the gathered literature to identify gaps in current research and systems. This analysis will inform the development of unique features and functionalities for the project.	A detailed analysis of identified gaps and how the project aims to address them.	Potential for incomplete identification of gaps due to limited literature.	1 week
Identify and document functional analysis	According to the analysis on the identified gap, functional and non-functional	Functional and non-functional requirements	Some requirements that will satisfy the project	1 week

	requirements of the application will be documented.	will of the application.	objectives could be missed	

Methodology Development (5 Weeks)

Work/Activities	Description	Deliverables	Risk Factors	Duration
Propose the Methodology	During this phase, the primary focus is on developing a comprehensive and detailed methodology for the project. This involves integrating both lexicon-based methods and advanced machine learning techniques to ensure a robust and effective sentiment analysis system. The methodology will outline the selection of appropriate tools, frameworks, and models, including VADER for initial sentiment scoring, CNNs for feature	A detailed methodology document outlining the proposed approach, tools, and techniques. Initial designs of use cases, system's activities, and entity relationships of data.	• The proposed methodology might be overly complex or infeasible given the project's scope and duration. • The integration of multiple techniques and tools could lead to unforeseen compatibility issues or increased complexity.	3 weeks

	extraction, and LSTMs for capturing long-term dependencies. Additionally, the methodology will detail the use of ensemble techniques to improve the accuracy of the sentiment analysis. The steps also include the initial design of the system's use cases, activities of admin and users, and entity-relationship of data to provide a clear structure and flow for the system's functionalities.			
Review the Methodology	After proposing the initial methodology, it is essential to review and refine it based on constructive feedback from	• A finalized methodology document that incorporates feedback and improvements.	• Potential delays in receiving feedback from reviewers.	2 weeks

	peers, supervisors, and other stakeholders. This review process ensures that the methodology is both robust and feasible, and aligns closely with the project's objectives. Feedback may highlight areas of improvement, including the simplification of complex processes, the selection of more suitable tools, or adjustments in the approach to better meet the project's goals. The refinement process will also involve detailed work on the system's use cases, activities, and entity-relationship to ensure they accurately represent the system's	• Refined Use Cases, system's activities, and entity relationships.	• The need to incorporate extensive revisions based on feedback, which could extend the duration of this phase.	

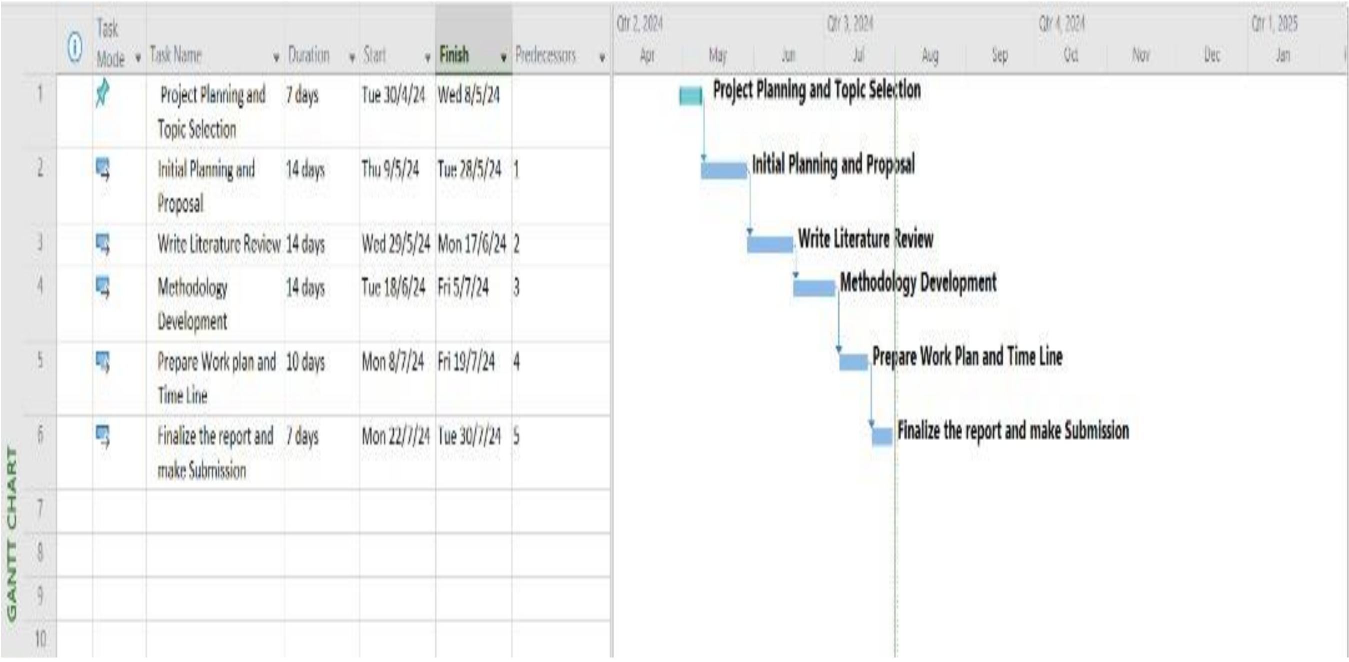
	requirements and functionalities.			

Prepare Work Plan and Time Line (1 week)

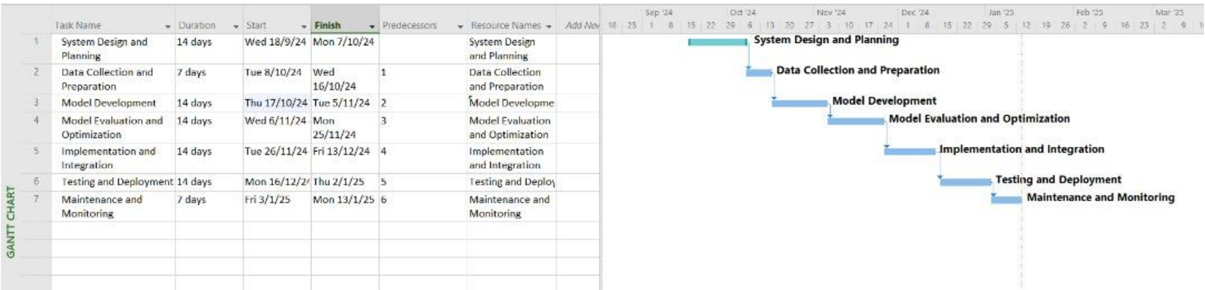
Work/Activities	**Description**	**Deliverables**	**Risk Factors**	**Duration**
Prepare Work Plan and Gantt Chart	Update the work plan and Gantt chart to reflect the refined methodology. Ensure all activities, dependencies, and timelines are accurately represented.	An updated work plan and Gantt chart with all dependencies and sequences clearly indicated.	Inaccurate time estimates and dependencies might need further adjustments.	1 week

4.2 Timeline

Gantt Chart for CP1



Gantt Chart for CP2



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